PROCEEDINGS THE 5th INTERNATIONAL CONFERENCE ON ECONOMICS, BUSINESS, AND MANAGEMENT RESEARCH (ICEBMR)
"Digital Economy, Human Dignity, and Inclusive Transformation in Asia"
https://econference.usd.ac.id/index.php/ICEBMR | ISSN: 3032-596X | Vol 5, 2026

INTEGRATING VOLUME AND OPEN INTEREST SCREENING WITH TECHNICAL ANALYSIS FOR CRYPTOCURRENCY TRADING: EVIDENCE FROM REAL-TIME TRADING ACTIVITY

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DOI: https://doi.org/10.24071/icebmr.v5i1.392

Abstract
High volatility and an overwhelming selection of digital assets make systematic decision-making difficult for cryptocurrency traders. To address this challenge, this study evaluates the empirical effectiveness of a multi-stage trading strategy that combines liquidity screening with multi-timeframe technical analysis. Using a quantitative descriptive approach, the model filters assets based on 24-hour Open Interest changes, trading volume, and market capitalization before applying price action, Exponential Moving Averages, and the Stochastic Momentum Index to confirm trade entries. Unlike traditional studies relying solely on backtested simulations, this research evaluates actual execution data collected between July 2025 and February 2026. Across 117 real-time trades, the strategy achieved a 62% win rate, yielding a 31% cumulative net return and a total profit of $195.09. These results demonstrate that combining volume and open interest indicators as a pre-selection mechanism significantly enhances trade quality by focusing technical execution on assets with active market participation. Overall, the findings highlight that integrating quantitative liquidity filters with structured technical analysis and strict risk management provides a viable, disciplined approach to navigating volatile crypto markets.
Keywords: *Cryptocurrency Trading, Technical Analysis, Open Interest, Volume Screening, Risk Management*

1. Introduction

The cryptocurrency market has experienced rapid growth in recent years, attracting increasing interest from investors and traders worldwide. Cryptocurrencies function not only as digital payment instruments but also as investment assets that offer substantial return potential. However, the cryptocurrency market is characterized by a high degree of volatility, resulting in substantial price fluctuations over relatively short periods. While these fluctuations create opportunities for significant returns, they also expose market participants to considerable risks of financial loss. Consequently, developing an effective trading strategy is essential for identifying market opportunities while maintaining appropriate risk control.

In addition to its high volatility, the cryptocurrency market comprises a large and continuously expanding number of digital assets, making it challenging for traders to determine which assets warrant further analysis. Conducting a comprehensive analysis of all available cryptocurrency assets is neither practical nor efficient. Therefore, an initial asset-screening process is required to identify assets that demonstrate relatively high levels of market activity and liquidity. In this study, asset selection is conducted using three primary indicators: 24-hour open interest change (OI Change 24h), trading volume, and market capitalization. These indicators are employed to identify cryptocurrency assets with substantial market activity before further technical analysis is performed.

Following the asset-screening process, this study evaluates a trading strategy that integrates market activity indicators with technical analysis and risk management. The proposed strategy combines volume and open interest screening with price action analysis, the Exponential Moving Average (EMA), the Stochastic Momentum Index (SMI), breakout strategies, and multi-time-frame analysis. These technical components are complemented by risk management techniques to control potential losses and improve the consistency of trading decisions. The integration of these approaches is intended to provide a systematic framework for identifying trading opportunities in highly volatile cryptocurrency markets.

Based on the background and research gap described above, this study addresses three primary research questions. First, how effective is a trading strategy that combines volume and open interest screening with technical analysis in the cryptocurrency market? Second, to what extent can asset screening based on market activity indicators improve the quality of trading decisions? Third, how does the proposed strategy perform when applied to actual trading data under volatile cryptocurrency market conditions?

In accordance with the research questions, this study aims to evaluate the effectiveness of a trading strategy that integrates asset screening with technical analysis in the cryptocurrency market. Specifically, the study seeks to assess the effectiveness of combining volume and open interest indicators with technical analysis techniques in identifying potential trading opportunities. In addition, the study evaluates the contribution of trading volume and open interest to the asset-selection process and examines whether these indicators can improve the quality of subsequent trading analysis and decision-making. Finally, the study aims to measure the performance of the proposed strategy based on actual trading results, particularly under volatile cryptocurrency market conditions, while considering the role of risk management in controlling potential losses.

2. Literature Review

2.1 Cryptocurrency and Market Characteristics

Cryptocurrencies are digital assets that operate primarily through blockchain technology and decentralized networks, reducing reliance on traditional financial intermediaries. Since the introduction of Bitcoin, cryptocurrencies have developed from an alternative digital payment concept into a broader asset class that is actively traded in global financial markets (Nakamoto, 2008). Bitcoin and other cryptocurrencies have increasingly attracted investors because of their potential for substantial returns, although their investment characteristics differ considerably from those of traditional financial assets. Baur et al. (2018), for example, found that Bitcoin exhibited characteristics more consistent with a speculative investment than with a conventional medium of exchange.

A defining characteristic of the cryptocurrency market is its high volatility. Cryptocurrency prices can experience substantial increases or declines over relatively short periods, creating opportunities for traders while simultaneously increasing exposure to market risk. The market is also distinguished by continuous 24-hour trading, high participation from speculative traders, and strong sensitivity to changes in investor sentiment. Research by Catania et al. (2018) and Enoksen et al. (2020) highlights the importance of instability and changing market conditions in understanding cryptocurrency price dynamics. Furthermore, cryptocurrency prices may respond to developments in broader financial markets, macroeconomic conditions, monetary policy, geopolitical events, and changes in the price of Bitcoin, which remains a dominant asset within the cryptocurrency ecosystem (Corbet et al., 2018; Liu & Tsyvinski, 2021).

The speculative characteristics of cryptocurrency markets are particularly relevant to technical trading strategies. Because prices can change rapidly in response to shifts in market sentiment and trading activity, traders require mechanisms for identifying assets that demonstrate sufficient liquidity and market participation. Consequently, market-based indicators such as trading volume and open interest can provide additional information regarding the intensity of trading activity before technical analysis is applied.

2.2 Technical Analysis

Technical analysis refers to an approach to financial market analysis that evaluates historical price and trading data to identify patterns, trends, momentum, and potential future price movements. The fundamental premise of technical analysis is that information reflected in market activity may be incorporated into observable price and volume movements. Lo et al. (2000) demonstrated that certain technical patterns contain potentially useful information for financial-market analysis, while Park and Irwin (2007) documented substantial academic

interest in the profitability and predictive ability of technical trading strategies. Technical analysis has therefore remained an important approach among market participants, particularly in markets characterized by frequent price movements and high trading activity.

In the context of cryptocurrency trading, this study applies several complementary technical-analysis approaches, including price action, support and resistance, breakout analysis, moving averages, momentum indicators, and multi-time-frame analysis. The combination of these techniques is intended to reduce reliance on a single indicator and provide a more comprehensive assessment of market conditions.

2.3 Price Action and Market Structure

Price action analysis focuses on the movement of market prices without relying exclusively on mathematical indicators. It can be used to identify market structure through a sequence of higher highs (HH), higher lows (HL), lower highs (LH), and lower lows (LL). A sequence of higher highs and higher lows generally indicates an upward market structure, whereas lower highs and lower lows indicate a downward structure. Changes in these patterns may provide information regarding potential trend continuation or reversal (Murphy, 1999).

In addition to identifying highs and lows, price action analysis can incorporate concepts such as Break of Structure (BoS) and Change of Character (ChoCh). A Break of Structure refers to a price movement that breaks an established structural high or low, potentially indicating continuation of the prevailing trend. A Change of Character refers to a shift in price behavior that may provide an early indication of a transition from one market structure to another. These concepts are used in this study to establish the prevailing market direction and identify potential changes in market structure before an entry decision is considered.

Support and resistance represent important price levels or zones at which buying and selling pressure may influence subsequent price movements. Support generally refers to an area where buying pressure may emerge and limit further price declines, whereas resistance represents an area where selling pressure may restrict further price increases (Murphy, 1999). These levels can function as potential reaction zones, including areas where prices may rebound or where a breakout may occur.

Within the proposed trading strategy, support and resistance are used to identify areas of interest before an entry is considered. Rather than treating these levels as fixed prices, the analysis considers them as zones in which market participants may respond to changes in supply and demand. This approach is particularly relevant in volatile cryptocurrency markets, where prices may temporarily move beyond a level before either continuing the breakout or returning to the previous trading range.

2.4 Breakout Strategy

A breakout strategy seeks to identify trading opportunities when the price moves beyond an established support or resistance level. A breakout may indicate that the balance between buying and selling pressure has shifted and that a new price movement may develop. However, not every breakout necessarily results in sustained price movement. Consequently, confirmation from price structure, volume, momentum, and higher-time-frame conditions can be used to distinguish potentially meaningful breakouts from false breakouts.

In this study, breakout analysis is integrated with price action, volume, EMA, SMI, and multi-time-frame analysis. The purpose of this integration is to increase the reliability of entry decisions by requiring multiple forms of confirmation rather than relying solely on the occurrence of a price-level breakout.

2.5 Multi-Time-Frame Analysis

Multi-time-frame analysis involves examining the same asset across different time

horizons to obtain a hierarchical view of market conditions. A top-down approach begins with a higher time frame to establish the broader market direction and subsequently moves to lower time frames to identify more precise trading setups and entry points (Murphy, 1999).

This study applies three time frames. The **daily timeframe** is used to determine the primary market direction and broader trend. The **4-hour (H4) timeframe** is then used to assess market structure and identify potential trading setups. Finally, the **15-minute (M15) timeframe** is used to obtain more precise entry confirmation. This approach is intended to ensure that short-term trading decisions remain consistent with the broader market structure.

2.6 Technical Indicators: Exponential Moving Average and Stochastic Momentum Index

The Exponential Moving Average (EMA) is a trend-following indicator that assigns greater weight to more recent price observations. Compared with a simple moving average, the EMA responds more quickly to recent changes in price, making it useful for identifying short- to medium-term changes in market direction.

This study employs the **13-period EMA (EMA 13)** and **21-period EMA (EMA 21)** to identify trend direction and establish market bias. The relationship between the two moving averages can provide information regarding the prevailing trend, while the EMA lines may also function as dynamic areas of support or resistance. Moving-average techniques are widely used in technical analysis because they provide a relatively simple mechanism for smoothing price fluctuations and identifying underlying trends (Murphy, 1999; Smit et al., 2023).

The Stochastic Momentum Index (SMI) is a momentum-based technical indicator that can be used to assess the position of the current closing price relative to a recent price range. Momentum indicators are commonly used to identify potential overbought and oversold conditions and to assess the strength of prevailing price movements (Dongrey, 2022).

In this study, the SMI is used primarily as a confirmation indicator rather than as a standalone trading signal. Specifically, the indicator is employed to evaluate momentum conditions and provide additional confirmation before an entry is executed. The use of SMI alongside price action, EMA, and support or resistance is intended to reduce the possibility of entering trades based solely on a single technical signal.

2.7 Trading Volume and Open Interest

Trading volume represents the quantity of an asset traded during a specified period and provides information regarding the intensity of market participation. Volume is an important component of technical analysis because changes in trading activity may provide additional information about the strength of price movements. In cryptocurrency markets, Balcilar et al. (2017) found that trading volume contains information relevant to Bitcoin returns at certain points of the conditional distribution, although its predictive relationship with returns is nonlinear and varies across market regimes.

Open interest, particularly in cryptocurrency derivatives markets, represents the number of outstanding derivative contracts that remain open. Changes in open interest can provide information regarding the level of participation and capital committed to derivative positions. When considered together with price and trading volume, changes in open interest may provide additional information regarding market positioning and trading activity. Research on cryptocurrency derivatives has highlighted the importance of derivatives markets in price discovery and broader market dynamics (Alexander et al., 2020).

In this study, trading volume and 24-hour open interest change (OI Change 24h) are used during the initial asset-screening stage. Assets exhibiting relatively high changes in open interest, substantial trading volume relative to market capitalization, and increasing overall market activity are prioritized for further technical analysis. This screening process is intended

to narrow the universe of cryptocurrency assets to those demonstrating sufficient market activity and potentially greater trading opportunities.

2.8 Risk Management

Risk management represents an essential component of systematic trading because the identification of profitable opportunities does not eliminate the possibility of adverse price movements. In highly volatile cryptocurrency markets, inappropriate position sizing or insufficient control of downside risk may result in substantial losses. Therefore, this study incorporates several risk-management mechanisms into the trading strategy.

First, stop-loss levels are determined based on relevant price structures to limit potential losses when the market moves against the trading position. Second, the strategy applies a minimum risk-reward ratio of **1:1**, ensuring that the potential reward is not lower than the predefined level of risk. Third, partial take-profit mechanisms are used to secure a portion of realized gains while allowing the remaining position to potentially benefit from continued price movement. Fourth, the break-even mechanism may be applied after sufficient price movement in favor of the position to reduce exposure to subsequent losses. Finally, the **1.618 Fibonacci Extension** is employed as an advanced potential target for identifying extended price objectives.

The integration of these risk-management techniques is intended to ensure that trading performance is evaluated not solely on the basis of winning trades but also in terms of the ability to control losses and preserve trading capital.

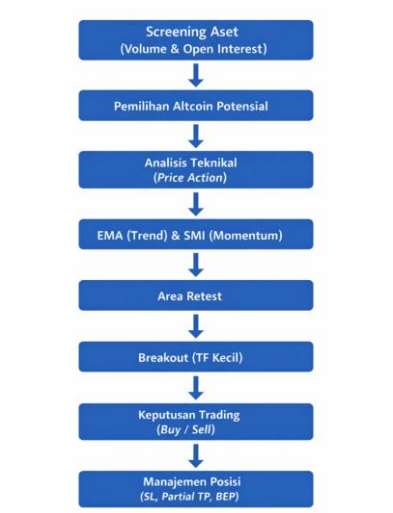


Figure 1. Research Framework and Process

3. Research Framework

Based on the literature discussed above, this study proposes an integrated trading framework consisting of several sequential stages. The first stage is **asset screening**, in which trading volume, market capitalization, and 24-hour open interest changes are evaluated to identify assets with relatively high market activity. The second stage involves **technical analysis**, incorporating price action, support and resistance, breakout analysis, EMA, SMI, and multi-time-frame analysis. The third stage involves **trading decision-making**, in which potential entry opportunities are evaluated based on the convergence of the identified signals. The fourth stage involves **risk management**, including stop-loss placement, risk-reward assessment, partial take-profit, break-even management, and Fibonacci Extension targets. The final stage involves **performance evaluation**, in which the actual trading results are assessed to determine the effectiveness of the proposed strategy.

The novelty of this study lies primarily in the integration of market-activity screening, technical analysis, multi-time-frame confirmation, and risk management within a single systematic

cryptocurrency trading framework. Previous research has examined technical analysis, cryptocurrency market behavior, trading volume, and individual technical indicators from different perspectives (Balcilar et al., 2017; Lo et al., 2000; Nti et al., 2020; Park & Irwin, 2007). However, this study combines **volume and open-interest screening**, **price-action-based market-structure analysis**, **EMA and SMI indicators**, **breakout analysis**, **multi-time-frame confirmation**, and **explicit risk-management rules** into an integrated trading procedure.

A further contribution of the study is its evaluation using **actual trading activity rather than relying exclusively on historical backtesting or simulated trading environments**. This distinction is important because actual trading involves execution-related considerations and behavioral responses that may not be fully captured by historical simulations. Therefore, the study seeks to provide empirical evidence regarding how an integrated screening and technical-analysis framework performs under actual cryptocurrency market conditions.

4. Research Methods

This study employed a quantitative research approach with descriptive-analytical methods to evaluate the performance of an integrated cryptocurrency trading strategy. The analysis was based on actual trading activity conducted under real market conditions rather than solely on historical simulations or backtesting. The use of actual trading data enables the study to capture market phenomena that may be difficult to reproduce in simulated environments, including false breakouts, sudden changes in market sentiment, high volatility, and changes in market momentum. The use of technical analysis and systematic trading rules is consistent with previous research demonstrating the relevance of price, volume, and technical indicators in financial-market analysis (Lo et al., 2000; Park & Irwin, 2007; Nti et al., 2020).

The research was conducted over the period from **July 17, 2025, to February 9, 2026**. This period was selected to capture trading activity across varying cryptocurrency market conditions, including periods of changing volatility, market momentum, and investor sentiment. The relatively extended observation period also provides an opportunity to evaluate the consistency of the proposed trading strategy across different market conditions rather than relying on a single short-term market episode.

5. Research Data and Sources

The study utilized primary trading data obtained from actual cryptocurrency futures transactions conducted during the research period. Additional market information was obtained from cryptocurrency trading platforms, CoinGlass, asset-change detail records, and cryptocurrency futures transaction data. These data sources were used to obtain information concerning price movements, trading volume, open interest, market capitalization, and transaction outcomes.

The use of market activity variables such as trading volume and open interest is supported by previous research indicating that trading activity can provide information relevant to cryptocurrency price dynamics. Balcilar et al. (2017), for example, examined the relationship between Bitcoin trading volume, returns, and volatility, demonstrating that volume contains information relevant to cryptocurrency market behavior. Similarly, research on cryptocurrency derivatives highlights the importance of derivatives-market activity for understanding price discovery and market dynamics (Alexander et al., 2020).

6. Research Procedures

The research procedure consisted of several sequential stages designed to systematically identify and evaluate trading opportunities. The first stage involved **asset screening** based on 24-hour open interest change (OI Change 24h), market capitalization, and the Volume-to-Market-Capitalization (VMC) ratio. The purpose of this screening stage was to narrow the large universe of cryptocurrency assets to those exhibiting relatively high levels of market activity. Volume provides an indication of trading intensity, while open interest provides information concerning

outstanding positions in the derivatives market. The combination of these indicators was therefore used as an initial filter before conducting more detailed technical analysis.

The second stage involved **market-structure analysis using price action**. The analysis considered the formation of higher highs, higher lows, lower highs, and lower lows to determine the prevailing market structure. Break of Structure (BoS) and Change of Character (ChoCh) were also considered when evaluating potential changes in market direction. Price-action analysis has long been used in technical analysis to identify trends and market patterns based on historical price movements (Lo et al., 2000; Murphy, 1999).

The third stage involved identifying the prevailing trend using the **Exponential Moving Average (EMA)**. Specifically, EMA 13 and EMA 21 were used to assess trend direction and establish market bias. The EMA was also considered as a dynamic support or resistance area. Moving-average techniques are widely used to smooth price fluctuations and identify underlying trends, although their effectiveness may vary according to market conditions (Murphy, 1999; Smit et al., 2023).

The fourth stage involved **momentum confirmation using the Stochastic Momentum Index (SMI)**. The SMI was used to evaluate momentum conditions and identify potential overbought or oversold situations. Rather than functioning as an independent trading signal, the indicator was used as a confirmation tool alongside price action and EMA analysis. The use of multiple technical indicators is consistent with the broader literature on technical analysis, which emphasizes the importance of evaluating price and market information from complementary perspectives (Dongrey, 2022; Nti et al., 2020).

The fifth stage consisted of **multi-time-frame analysis**. A top-down approach was employed in which the daily timeframe was used to establish the broader market direction, the H4 timeframe was used to assess market structure and identify potential trading setups, and the M15 timeframe was used to seek more precise entry confirmation. This approach was intended to align short-term trading decisions with the broader market trend and reduce the likelihood of entering positions that conflict with higher-time-frame market conditions.

The sixth stage involved determining the **entry point, stop-loss level, and take-profit target**. Entry decisions were made only after the relevant technical conditions and confirmation signals were identified. Stop-loss levels were determined according to market structure to limit potential losses, while take-profit targets were established based on predefined risk-reward considerations and relevant technical levels. Partial profit-taking, break-even adjustments, and Fibonacci Extension targets were also incorporated into the trading process where applicable.

The final stage involved **evaluating the actual trading results**. Each completed transaction was classified as either profitable or unprofitable, and overall performance was evaluated using indcators including the total number of transactions, number of profitable and losing transactions, win rate, total profit, profit percentage, and average profit per trade.

The study evaluated the performance of the proposed trading strategy using actual cryptocurrency trading results recorded during the research period. Before technical analysis was conducted, cryptocurrency assets were screened according to 24-hour Open Interest Change, market capitalization, and the Volume-to-Market-Capitalization (VMC) ratio. This screening process was designed to prioritize assets exhibiting relatively high market activity and therefore reduce the number of assets requiring detailed technical analysis.

The screening process was followed by market-structure analysis using price action, including the identification of trend structure, support and resistance levels, and potential breakout conditions. EMA 13 and EMA 21 were subsequently used to identify trend direction and market bias, while the SMI was employed to provide additional momentum confirmation. The integration of these

indicators allowed the trading strategy to evaluate potential opportunities from several complementary perspectives rather than relying on a single technical indicator.

For example, the screening process identified **AIGENSYN** as an asset exhibiting a substantial increase in trading volume and open interest. Following the screening stage, the asset was analyzed using market structure, support areas, EMA, and SMI before a trading entry was considered. This example illustrates the sequential nature of the proposed methodology, in which market-activity screening precedes technical analysis and trading execution.

7. Research Findings and Discussion

7.1 Trading Performance

The trading results obtained during the research period are summarized in Table 1.

Table 1. Trading Results Statistics

Indicator	Result
Total Transactions	117
Profitable Transactions	73
Losing Transactions	44
Win Rate	62%
Total Profit	USD 195.09
Profit Percentage	31%
Average Profit per Trade	USD 1.67

The strategy generated **117 transactions**, consisting of **73 profitable transactions and 44 losing transactions**, resulting in a reported win rate of approximately **62%**. The strategy generated a total profit of **USD 195.09**, corresponding to a reported profit percentage of **31%**, with an average profit of approximately **USD 1.67 per transaction**.

The win rate indicates that profitable transactions represented the majority of executed trades during the observation period. However, the win rate alone should not be interpreted as conclusive evidence of strategy superiority. Trading performance should also be evaluated in relation to risk-reward ratios, transaction costs, drawdowns, position sizing, and other measures of risk-adjusted performance. Previous research on technical analysis emphasizes that apparent profitability can vary depending on market conditions, transaction costs, and methodological assumptions (Park & Irwin, 2007). Therefore, the 62% win rate provides evidence of the observed trading performance during the study period but does not, by itself, establish that the strategy will consistently outperform alternative strategies or market benchmarks.

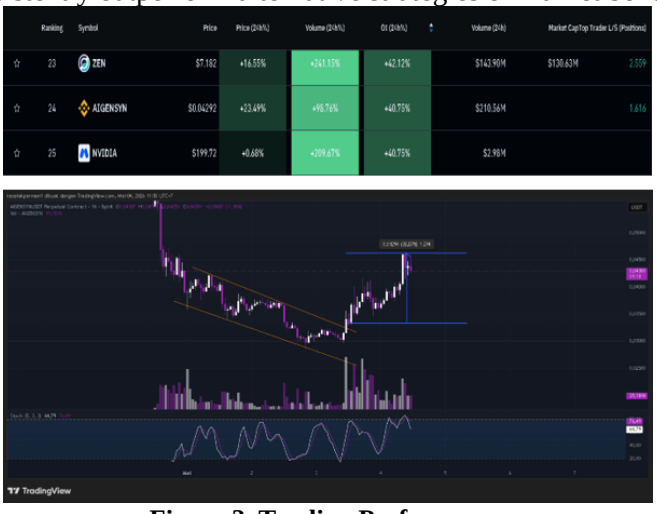


Figure 2. Trading Performance

7.2 Discussion of Strategy Performance

The observed performance suggests that the integration of asset screening and technical analysis may provide a systematic approach to identifying cryptocurrency trading opportunities. The initial screening process using volume, open interest, and market capitalization reduced the number of assets requiring further analysis and directed attention toward assets exhibiting relatively high market activity. This approach is theoretically consistent with evidence that trading volume contains information regarding cryptocurrency market dynamics (Balcilar et al., 2017).

The subsequent integration of **price action, EMA, SMI, volume, open interest, and multi-time-frame analysis** provided several layers of confirmation before trading decisions were executed. Price action was used to determine market structure, while EMA was used to establish the prevailing trend and market bias. The SMI provided additional information regarding momentum, while volume and open interest were used to assess the level of market activity. Multi-time-frame analysis then helped align the entry decision with the broader market direction.

The use of multiple forms of technical information is consistent with the broader literature on technical analysis. Lo et al. (2000) demonstrated that certain technical patterns may contain information relevant to future price movements, while Park and Irwin (2007) noted that the profitability of technical analysis has been documented across different markets and periods, although the evidence is not uniformly conclusive. Nti et al. (2020) similarly emphasize the extensive use of technical indicators and analytical approaches in financial-market prediction research.

The role of trading volume is particularly relevant in the present strategy because an increase in trading activity may provide additional information regarding the strength and significance of price movements. Karpoff (1987) established the importance of the relationship between price changes and trading volume in financial-market research, while Balcilar et al. (2017) specifically examined the predictive relationship between Bitcoin volume, returns, and volatility. In the present study, volume was therefore not treated merely as a secondary indicator but as an initial screening variable for identifying assets with substantial market activity.

Open interest provided an additional dimension because it reflects activity in cryptocurrency derivatives markets. The combination of open interest and volume may provide a broader representation of market participation than either variable considered independently. Research by Alexander et al. (2020) highlights the relevance of cryptocurrency derivatives markets to price discovery, informational efficiency, and market dynamics. Accordingly, incorporating open interest into the initial screening process provides a potentially useful mechanism for identifying assets experiencing changes in derivatives-market participation.

The results also suggest that the proposed strategy was able to operate under real cryptocurrency market conditions that included high volatility and rapidly changing market momentum. Unlike a purely historical backtest, actual trading activity exposes the strategy to real-time market conditions, including false breakouts, rapid sentiment changes, and unexpected price movements. These conditions are particularly relevant in cryptocurrency markets, which have been characterized by substantial volatility and periods of speculative activity (Baur et al., 2018; Corbet et al., 2018; Enoksen et al., 2020).

Overall, the findings provide preliminary evidence that an integrated approach combining **asset screening, price-action analysis, EMA, SMI, multi-time-frame analysis, and risk management** can generate a positive trading outcome during the specified observation period. Nevertheless, the results should be interpreted as evidence of the strategy's performance within the particular market conditions and observation period examined in this study. Further research using longer observation periods, multiple market regimes, benchmark comparisons, transaction-cost adjustments, and risk-adjusted performance measures would be necessary to

determine the robustness and generalizability of the strategy.

8. Conclusion

This study evaluated an integrated cryptocurrency trading strategy that combines asset screening, technical analysis, multi-time-frame analysis, and risk management under actual market conditions. The findings indicate that the proposed strategy generated a relatively favorable trading performance during the observation period from July 17, 2025, to February 9, 2026. The strategy generated 117 transactions, consisting of 73 profitable transactions and 44 losing transactions, resulting in a win rate of 62%, total profit of USD 195.09, and a reported return of 31%. These results provide preliminary evidence that the integration of market-activity screening and technical analysis can support systematic trading decisions in a highly volatile cryptocurrency market. However, the results should be interpreted within the specific market conditions and observation period examined rather than as evidence of universal or persistent profitability.

The asset-screening process using 24-hour Open Interest Change (OI Change 24h), market capitalization, and the Volume-to-Market-Capitalization (VMC) ratio played an important role in narrowing the large number of available cryptocurrency assets to those exhibiting relatively high market activity. Trading volume has been shown to contain information relevant to cryptocurrency returns and volatility, while derivatives-market activity can provide additional information regarding price discovery and market dynamics (Alexander et al., 2020; Balcilar et al., 2017). Accordingly, the findings suggest that combining volume and open interest as an initial screening mechanism can provide a practical basis for determining which assets should receive further technical analysis.

The study also found that the integration of price action, EMA, SMI, and multi-time-frame analysis provided multiple layers of confirmation before trading positions were initiated. Price action was used to identify market structure and potential changes in market direction, while EMA was used to determine trend direction and market bias. SMI provided additional momentum confirmation, and multi-time-frame analysis enabled short-term entry decisions to be considered within the context of broader market conditions. The use of multiple technical-analysis components is consistent with previous literature emphasizing the potential informational value of technical patterns and indicators in financial markets (Lo et al., 2000; Murphy, 1999; Nti et al., 2020).

Risk management was also an important component of the strategy. Stop-loss placement, risk-reward assessment, partial take-profit, and break-even mechanisms were incorporated to limit downside exposure and protect realized gains. This is particularly important in cryptocurrency markets because of their substantial volatility and susceptibility to rapid changes in market sentiment (Baur et al., 2018; Corbet et al., 2018; Enoksen et al., 2020). Therefore, the findings suggest that trading performance should not be evaluated solely according to the percentage of profitable transactions, but also according to the strategy's ability to control losses and maintain an acceptable relationship between risk and return.

Overall, the study concludes that the proposed combination of **asset screening, price action, EMA, SMI, multi-time-frame analysis, and risk management** provides a structured framework for cryptocurrency trading under volatile market conditions. Nevertheless, the observed results represent the performance of the strategy during a specific observation period and should not be interpreted as conclusive evidence that the strategy will consistently generate positive returns across all cryptocurrency market regimes.

8.1 Practical Implications

The findings have several practical implications for cryptocurrency traders. First, the results suggest that traders may benefit from conducting an initial asset-screening process before performing detailed technical analysis. The cryptocurrency market contains a large number of assets, making it inefficient to analyze every available asset individually. Screening based on OI Change 24h, market capitalization, and the VMC ratio provides a systematic

mechanism for prioritizing assets with relatively high levels of market activity. This approach is consistent with evidence that trading volume contains information concerning cryptocurrency market behavior (Balcilar et al., 2017).

Second, traders can consider combining multiple technical-analysis tools rather than relying on a single indicator. The use of price action, EMA, SMI, and multi-time-frame analysis allows trading decisions to incorporate information concerning market structure, trend direction, momentum, and broader market conditions. Such an approach may reduce dependence on isolated trading signals and encourage more systematic decision-making. Nevertheless, technical indicators should be regarded as decision-support tools rather than guarantees of future price movements, particularly because evidence concerning the profitability of technical analysis varies across markets and time periods (Park & Irwin, 2007).

Third, the findings emphasize the importance of risk management in cryptocurrency trading. Even when a trading strategy generates a relatively high win rate, individual trades remain exposed to adverse price movements. Cryptocurrency markets can experience rapid price changes associated with speculative activity, market sentiment, and broader financial-market developments (Baur et al., 2018; Corbet et al., 2018). Consequently, traders should establish stop-loss levels before entering positions and maintain predefined risk-reward parameters rather than allowing individual trading decisions to be determined entirely by short-term market movements.

Finally, traders should recognize the risks associated with false breakouts, sudden changes in market sentiment, and movements in Bitcoin that may influence other cryptocurrency assets. These risks reinforce the importance of continuously reassessing market structure and momentum rather than assuming that a previously identified trend will continue indefinitely. The use of multi-time-frame analysis may assist traders in maintaining consistency between short-term entries and broader market conditions.

8.2 Academic Implications

From an academic perspective, this study contributes to the literature on cryptocurrency trading by integrating several analytical dimensions that are frequently examined separately. The proposed framework combines **market-activity screening through volume and open interest, price-action analysis, moving-average analysis, momentum confirmation, multi-time-frame analysis, and risk management** within a single trading procedure. Previous studies have examined relationships between trading volume and cryptocurrency returns (Balcilar et al., 2017), cryptocurrency derivatives and price discovery (Alexander et al., 2020), and the broader effectiveness of technical-analysis approaches (Lo et al., 2000; Park & Irwin, 2007). This study extends these perspectives by applying the indicators as sequential components of an integrated trading strategy.

The study also contributes methodologically by evaluating the strategy using actual trading activity rather than relying exclusively on historical price simulations. Actual trading provides an opportunity to observe trading outcomes under real market conditions, including rapid price changes, false breakouts, and changing market momentum. Nevertheless, actual trading also introduces additional sources of variation, including execution conditions and trader decision-making, which should be considered when interpreting the results.

The findings further provide a basis for future quantitative testing of the individual contribution of each component of the strategy. Future researchers could statistically evaluate whether the inclusion of open interest, volume screening, EMA, SMI, or multi-time-frame confirmation produces statistically significant improvements in risk-adjusted performance. Such an approach would strengthen the distinction between a practically useful trading framework and a strategy whose observed performance may be attributable to particular market conditions.

8.3 Risk Analysis and Research Limitations

Despite generating a relatively favorable outcome during the observation period, the strategy remains exposed to several market and methodological risks. One important risk is the occurrence of **false breakouts**, in which prices temporarily move beyond a support or resistance level before reversing. Because breakout strategies rely on price movements through important technical levels, false breakouts may generate premature entries and subsequent losses. The use of additional confirmation through price action, volume, momentum, and multiple time frames can potentially reduce this risk, but it cannot eliminate it entirely (Lo et al., 2000; Murphy, 1999).

A second risk arises from **sudden changes in market sentiment**. Cryptocurrency prices can respond rapidly to market information and changes in investor expectations. Previous research has documented substantial volatility and changing dynamics within cryptocurrency markets (Catania et al., 2018; Enoksen et al., 2020). Consequently, technical conditions that appear favorable at the time of entry may change rapidly following unexpected information.

A third risk is the **influence of Bitcoin price movements on other cryptocurrency assets**. Bitcoin occupies a central position within the cryptocurrency ecosystem, and movements in major cryptocurrency assets can be associated with broader changes across the market. Research examining the relationships between cryptocurrencies and other financial assets demonstrates that cryptocurrency markets are interconnected with broader market dynamics (Corbet et al., 2018). Therefore, an apparently attractive setup on an individual altcoin may still be affected by broader market movements.

A fourth risk involves **extreme volatility caused by macroeconomic, monetary, or geopolitical developments**. Unexpected market information can produce price movements that exceed the assumptions underlying a technical setup. This reinforces the importance of stop-loss mechanisms and predefined risk-management rules. The importance of risk control is particularly relevant because cryptocurrency assets can exhibit substantial price fluctuations over relatively short periods (Baur et al., 2018; Liu & Tsyvinski, 2021).

Several methodological limitations should also be acknowledged. First, the identification of market structures, support and resistance zones, breakouts, and price-action patterns contains an element of analyst subjectivity. Although predefined analytical rules were used, some technical interpretations may differ between analysts. This limitation is consistent with the broader challenge of evaluating technical-analysis strategies, where methodology and implementation can influence reported results (Park & Irwin, 2007).

Second, because the study used actual trading data, the results may have been influenced by trader-related factors, including hesitation, fear, uncertainty, and execution decisions. Consequently, the observed performance cannot be attributed exclusively to the technical strategy itself. Third, the screening parameters were not subjected to a formal statistical optimization process. The selected thresholds and indicators were therefore based on the research framework rather than being optimized through an independent statistical procedure.

Fourth, the study was conducted over a relatively specific observation period. Cryptocurrency market conditions can change considerably across bullish, bearish, sideways, and high-volatility regimes. Therefore, the observed 62% win rate and 31% reported return may not be replicated under different market conditions. Previous research has similarly emphasized the instability of cryptocurrency market dynamics, which complicates the generalization of findings from one period to another (Catania et al., 2018).

Finally, the study primarily evaluates performance using transaction-level outcomes, including win rate, total profit, and average profit per trade. Although these measures provide useful information, a more comprehensive evaluation would include additional risk-adjusted

metrics such as maximum drawdown, Sharpe ratio, Sortino ratio, profit factor, expectancy, and transaction costs. Consequently, future research should incorporate these measures to provide a more complete assessment of strategy performance.

8.4 Recommendations for Future Research

Future research should extend the observation period to include different cryptocurrency market regimes, including bullish, bearish, sideways, and extreme-volatility periods. A longer observation period would allow researchers to determine whether the observed performance is persistent across different market environments rather than being specific to the conditions during July 2025–February 2026.

Future studies could also compare the proposed strategy with alternative technical indicators, such as the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands, and volatility-based indicators. Such comparisons would allow researchers to determine whether the current combination of EMA and SMI provides additional predictive or practical value relative to alternative technical configurations.

Another potential direction is the development of an **automated asset-screening and trading system**. The current framework could be translated into predefined computational rules for volume, open interest, market structure, momentum, and entry confirmation. This would reduce analyst subjectivity and make the strategy more suitable for quantitative testing. Such an approach would also allow researchers to conduct systematic robustness tests and out-of-sample evaluations.

Future research should also incorporate **risk-adjusted performance measures and transaction costs**. A strategy with a high win rate may not necessarily be economically superior if its losing trades are substantially larger than its winning trades or if trading costs materially reduce profitability. Park and Irwin (2007) emphasize the importance of methodological considerations, including transaction costs and data-snooping issues, when evaluating technical trading profitability.

Finally, the proposed framework could be tested across other financial markets, including equities, foreign exchange, commodities, and cryptocurrency derivatives. Cross-market testing would provide evidence regarding whether the combination of market-activity screening and technical analysis represents a broadly applicable trading framework or whether its effectiveness is primarily associated with the characteristics of cryptocurrency markets.

References

Alexander, C., Choi, J., Park, H., & Sohn, S. (2020). BitMEX Bitcoin derivatives: Price discovery, informational efficiency, and market dynamics. *Journal of Futures Markets, 40*(8), 1237–1256.

Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling, 64*, 74–81.

Barberis, N., & Thaler, R. H. (2003). A survey of behavioral finance. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), *Handbook of the economics of finance* (Vol. 1, pp. 1053–1128). Elsevier.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money, 54*, 177–189.

Bulkowski, T. N. (2005). *Encyclopedia of chart patterns* (2nd ed.). Wiley.

Catania, L., Grassi, S., & Ravazzolo, F. (2019). Forecasting cryptocurrencies under model and parameter instability. *International Journal of Forecasting, 35*(2), 485–501.

Corbet, S., Lucey, B., & Yarovaya, L. (2019). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters, 26*, 81–88.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters, 165*, 28–34.

Dongrey, S. (2022). Study of market indicators used for technical analysis. *International Journal of Engineering and Management Research, 12*(2), 64–83.

Enoksen, F. A., Landsnes, C. J., Lucivjanska, K., & Molnár, P. (2020). Understanding risk of bubbles in cryptocurrencies. *Journal of Economic Behavior & Organization, 176*, 129–144.

Fong, W. M., Wong, W. K., & Lean, H. H. (2005). International momentum strategies: A stochastic dominance approach. *Journal of Financial Markets, 8*(1), 89–109.

Grimes, A. (2012). *The art and science of technical analysis: Market structure, price action, and trading strategies*. Wiley.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decisions under risk. *Econometrica, 47*(2), 263–291.

Karpoff, J. M. (1987). The relation between price changes and trading volume: A survey. *Journal of Financial and Quantitative Analysis, 22*(1), 109–126.

Liu, Y., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies, 34*(6), 2689–2727.

Liyanto, A. (2012). Technical analysis to get profit in online forex trading. *Journal of Economics, 17*(2).

Lo, A. W. (2005). Reconciling efficient markets with behavioral finance: The adaptive markets hypothesis. *Journal of Investment Consulting, 7*(2), 21–44.

Lo, A. W., Mamaysky, H., & Wang, J. (2000). Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *The Journal of Finance, 55*(4), 1705–1765.

Mahendra, K., Satyahadewi, N., & Perdana, H. (2022). Technical analysis of stocks using the MACD indicator. *Scientific Bulletin of Mathematics, Statistics and Its Applications (BIMASTER), 11*.

Murphy, J. J. (1999). *Technical analysis of the financial markets: A comprehensive guide to trading methods and applications*. New York Institute of Finance.

Nakamoto, S. (2008). *Bitcoin: A peer-to-peer electronic cash system*.

Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A systematic review of fundamental and technical analysis of stock market predictions. *Artificial Intelligence Review, 53*, 3007–3057.

Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance, 53*(5), 1775–1798.

Park, C.-H., & Irwin, S. H. (2007). What do we know about the profitability of technical analysis? *Journal of Economic Surveys, 21*(4), 786–826.

Smit, A. C., Schat, E., & Ceulemans, E. (2023). The exponentially weighted moving average procedure. *Assessment, 30*(5), 1354–1368.

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters, 148*, 80–82.