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Evaluating Technical Trend Filters for a Bollinger Band Breakout-and-Reversal Strategy Across Multiple Timeframes Empirical comparison of seven technical trend filters across five BTCUSD timeframes 15 October 2026

Venkata Maheswara Rao Atchula

avmrao2002@gmail.com

Nirwan University

Dr. Pawan Kumar Pareek

Nirwan University

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Evaluating Technical Trend Filters for a Bollinger Band Breakout-and-Reversal Strategy Across Multiple Timeframes

Empirical comparison of seven technical trend filters across five BTCUSD timeframes

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*Venkata Maheswara Rao Atchula, Research Scholar, avmrao2002@gmail.com, Nirwan University, Jaipur, Rajasthan, India

*Corresponding author: avmrao2002@gmail.com

Pawan Kumar Pareek, Professor, miracle.pareek@gmail.com, Nirwan University, Jaipur, Rajasthan, India

Abstract

This study evaluates whether technical trend filters improve a Bollinger Band breakout-and-reversal strategy on BTCUSD across multiple chart timeframes. Seven filters—EMA, EMA200, Supertrend, moving-average crossover, MACD Trend, ADX Trend, and Renko HH-HL—are compared with an unfiltered baseline at five timeframes: 1 minute, 3 minutes, 5 minutes, 15 minutes, and 1 hour. The 40 configurations are evaluated using exported historical backtest metrics, including closed-trade net profit, profit factor, trade count, commission, and maximum intrabar drawdown. The moving-average crossover filter produces the strongest relative improvement over its matched baseline at each tested timeframe and reduces trade frequency by approximately 82–85%. Nevertheless, all filtered configurations remain net-negative at 1, 3, and 5 minutes. At 15 minutes, the moving-average crossover is the only filtered configuration with positive net profit; at 1 hour, the moving-average crossover, EMA, and Renko HH-HL configurations are positive. This pattern is consistent with the possibility that directional confirmation reduces exposure to unsuccessful short-horizon signals, but false breakouts were not separately labelled or directly measured. The study is exploratory and limited to one instrument, one approximately one-year historical period, fixed parameters, and 40 configurations. No untouched out-of-sample evaluation is documented, and the positive results are sensitive to drawdown and outlier-trade concentration. The results therefore indicate historical associations, not guaranteed or generalizable profitability.

Keywords: Algorithmic trading; Bitcoin; Bollinger Bands; Cryptocurrency markets; Technical analysis; Trend filters.

JEL Classification: C53; G14; G17.

1. Introduction

Technical trading systems frequently combine a price-based trigger with a trend filter intended to reduce entries against the prevailing market direction. Bollinger Bands provide a volatility-relative framework for identifying prices that extend beyond a moving-average envelope, while trend indicators attempt to distinguish directional markets from noisy or mean-reverting conditions. The value of a filter is not self-evident: a filter may reduce false entries and turnover, but it can also delay entry, omit profitable reversals, or concentrate results in a small number of trades.

This paper evaluates a Bollinger Band breakout-and-reversal strategy under a controlled comparison. The same base parameters, date window, order size, and transaction-cost assumptions are held constant while one of seven filters is activated at a time. Each filtered configuration is compared against an unfiltered baseline on the same timeframe. The aim is not to identify a universally profitable indicator, but to measure how filters change historical net profit, profit factor, trading frequency, costs, and drawdown across timeframes.

The study is exploratory. The experiments use BTCUSD, one historical period, and a fixed set of parameters. Some results are sensitive to unusually large trades, and the reported drawdowns are presented as descriptive risk metrics. Initial capital is a backtest configuration value, not a stop-out threshold or a criterion used to terminate or rank experiments.

2. Research questions

- RQ1: How does each trend filter change net profit and profit factor relative to the unfiltered baseline at the same timeframe?
- RQ2: To what extent do filters reduce trade frequency and commission expenditure?
- RQ3: Does the relative performance of filters vary across 1-minute, 3-minute, 5-minute, 15-minute, and 1-hour charts?
- RQ4: Are positive results robust to drawdown, outlier-trade concentration, and prospective out-of-sample evaluation?

3. Related work and conceptual framing

Bollinger Bands are a volatility-adaptive envelope built around a moving average and a dispersion measure [1]. Their use in a trading rule should be distinguished from a claim that a band touch or breach has predictive value on its own. Trend filters encode different hypotheses: EMA and EMA200 represent price relative to a smoothed trend; moving-average crossover represents a change in relative trend direction; MACD compares short- and long-horizon exponential averages; ADX estimates trend strength; Supertrend combines volatility and direction; and Renko HH-HL attempts to characterize directional price structure.

My empirical question builds on research that evaluates technical-analysis rules using explicit algorithms and statistical inference [2]. Transaction costs and data-snooping risks are especially important when many configurations are compared [3, 12]. Since this study evaluates 40 configurations on one historical window, results should be described as exploratory unless an untouched validation period and suitable statistical tests are added [4].

Recent cryptocurrency-specific evidence makes the present comparison especially relevant. Hudson and Urquhart [5] evaluate a large universe of technical rules across cryptocurrency markets and explicitly address data-snooping and out-of-sample performance. Svogun and Bazán-Palomino [6] show that transaction costs and bubble periods can materially affect the performance of moving-average and breakout rules, including at one-minute frequency. Related work examines high-frequency Bitcoin technical rules [7], trend-following rules in Bitcoin [8], and Bollinger Band strategies in Bitcoin futures [9]. More recent evidence by Deprez and Frömmel [10] evaluates a very large set of Bitcoin rules while accounting for transaction costs, data mining, and out-of-sample performance. These

studies motivate a controlled, matched-baseline comparison, while also showing why the present one-year, single-instrument results should remain descriptive until validated on an untouched sample.

4. Methods: Strategy and experimental design

4.1 Base strategy

The base system is the Bollinger Breakout Engine, using a Bollinger Band length of 20 and a multiplier of 2. The strategy supports long and short positions. The experiment compares the unfiltered rule with seven individually enabled trend filters. The exit policy is the strategy's existing reversal-based logic. The study does not add a separate fixed stop-loss, take-profit, or trailing-stop matrix; those controls are disabled in the exported experiment settings.

4.2 Filters and parameters

Filter	Recorded parameterization
EMA	EMA-based trend filter; the workbook records EMA length 50 in the EMA mode field.
EMA200	200-period EMA trend filter; retain as a separate filter from EMA.
Supertrend	ATR length 10 and multiplier 3 in the recorded configuration.
MA Crossover	Fast EMA 50; slow EMA 200.
MACD Trend	Fast 12; slow 26; signal 9.
ADX Trend	Length 14; threshold 20.
Renko HH-HL	ATR mode; ATR length 14; multiplier 1.

4.3 Timeframes and control group

The five chart timeframes are 1 minute, 3 minutes, 5 minutes, 15 minutes, and 1 hour. Each timeframe has one unfiltered baseline and seven filtered runs, giving 40 configurations in total. The matched comparison for a filter is its result minus the unfiltered result for the same timeframe. Raw dollar P&L is not compared across timeframes as though the observations had equivalent exposure or risk.

4.4 Execution assumptions

Item	Setting
Instrument	BTCUSD
Backtest window	14 October 2025 to 15 October 2026.
Initial capital	USD 10,000.
Order size	1 contract.
Pyramiding	1 order (recorded setting).
Commission	0.1%.
Slippage	10 ticks.
Fixed stop-loss	Off.
Fixed take-profit	Off.
Trailing stop	Off.
Exit policy	Existing reversal-based strategy logic.

I report P&L, commission, and drawdown as recorded in the exported backtests; I have not independently recalculated every trade from raw market data for this manuscript. Their economic interpretation depends on the BTCUSD symbol feed, point value and contract-size settings,

commission basis, and slippage implementation matching the intended evaluation. Before drawing conclusions about economic profitability, these settings and the exported totals must be reconciled against the TradingView Strategy Properties and trade-level records. The results are therefore treated as exploratory comparative outputs, not as evidence of deployable profitability.

5. Strategy development, signal logic, filters, and test configuration

5.1 Strategy implementation and entry logic

The tested system is based on Bollinger Breakout Engine, implemented in TradingView Pine Script v5. The Bollinger basis is the simple moving average of closing prices over 20 bars. The standard deviation is calculated over the same lookback, and the upper and lower bands are defined as the basis plus or minus two standard deviations. The band width therefore adapts to the recent dispersion of prices.

A long signal is generated when the confirmed bar closes above the upper Bollinger Band and the selected trend filter permits a long trade. A short signal is generated when the confirmed bar closes below the lower band and the selected filter permits a short trade. The script uses close-based conditions and declares process_orders_on_close=true and calc_on_every_tick=false. In the strategy logic, a new long signal closes an existing short position before submitting a long entry; a new short signal closes an existing long position before submitting a short entry. Thus, in the tested RM OFF configuration, the main exit mechanism is signal reversal rather than a fixed stop-loss, take-profit, or trailing stop.

The strategy supports additional execution and filtering modules, including volatility and range filters, market-structure confirmation, a multi-timeframe Renko direction vote, recent-high/low channel conditions, and session blackout windows. These are implementation capabilities of the wider script and should not be assumed to have contributed to the 40-run comparison unless the corresponding settings were enabled in the experiment exports. The experimental design isolates the selected trend-filter setting against an unfiltered baseline at each chart timeframe.

Code availability and reproducibility: The Pine Script source code for Bollinger Breakout Engine v4.2 is proprietary and is not publicly available. I therefore describe the tested entry logic, filter definitions, parameters, execution assumptions, and reported metrics in the manuscript, but I cannot provide the complete source code for independent execution. This restriction limits exact reproduction of the full strategy and should be considered when evaluating the findings.

5.2 Trend filters evaluated

Each filtered run applies one trend filter at a time. The filter is used as a directional gate on the Bollinger breakout signal; it does not replace the Bollinger entry trigger.

Filter	Rule for long signals	Rule for short signals
None (baseline)	No trend-direction gate	No trend-direction gate
EMA	Close above EMA(50)	Close below EMA(50)
EMA200	Close above EMA(200)	Close below EMA(200)
Supertrend	Supertrend indicates uptrend (stDir = −1 in script convention)	Supertrend indicates downtrend (stDir = +1 in script convention)
MA Crossover	EMA(50) above EMA(200)	EMA(50) below EMA(200)
MACD Trend	MACD line above zero	MACD line below zero
ADX Trend	+DI > −DI and ADX > 20	−DI > +DI and ADX > 20

Filter	Rule for long signals	Rule for short signals
Renko HH-HL	Last two generated Renko bricks both upward	Last two generated Renko bricks both downward

The EMA, EMA200, and MA Crossover cases are distinct tests: EMA uses price relative to the 50-period EMA, EMA200 uses price relative to the 200-period EMA, and MA Crossover compares the 50-period and 200-period EMAs directly. The Renko HH-HL implementation constructs synthetic brick directions from confirmed chart-bar closes using an ATR-derived brick size; it allows a direction only when the latest two stored bricks agree. This operational definition should be preserved when reproducing the experiment.

5.3 Recorded parameter settings

Table 5 summarizes the settings documented in the experiment records and the supplied Pine Script. The parameter values below describe the tested trend-filter variants; optional script modules are not treated as additional experimental factors in this study.

Component	Setting used / recorded	Interpretation
Bollinger Bands	Length 20; multiplier 2.0	Common entry trigger across configurations
Chart timeframes	1m, 3m, 5m, 15m, 1h	Eight configurations per timeframe: baseline plus seven filters
EMA filter	EMA length 50	Close compared with EMA(50)
EMA200 filter	EMA length 200	Close compared with EMA(200)
Supertrend	ATR length 10; multiplier 3.0	Direction filter
MA Crossover	Fast EMA 50; slow EMA 200	Fast/slow EMA relationship
MACD Trend	Fast 12; slow 26; signal 9	MACD line sign determines direction
ADX Trend	Length 14; threshold 20	DI direction plus ADX strength threshold
Renko HH-HL	ATR length 14; multiplier 1.0	Synthetic brick size is ATR × multiplier
Initial capital	USD 10,000	Recorded in strategy settings
Order sizing	Fixed quantity; 1 contract	Recorded in strategy settings
Commission	0.1%	Recorded in strategy settings
Slippage	10 ticks	Recorded in experiment workbook settings; verify against TradingView Strategy Properties
Pyramiding	1	Recorded in workbook settings
Exit policy	Fixed SL off; TP off; TSL off (RM OFF)	Position reversal is the principal strategy exit mechanism
Backtest window	14 October 2025 to 15 October 2026	Recorded test range
Instrument	BTCUSD	Confirmed by the researcher; CRUDEOILM is redundant Dhan configuration metadata

6. Evaluation metrics

The primary metric is closed-trade net profit after the strategy tester's reported costs. Profit factor is the ratio of gross profits to gross losses. Additional metrics include trade count, win rate, commission paid, Sharpe ratio, Sortino ratio, and maximum intrabar drawdown. Open P&L is reported separately and is not added to closed-trade net profit in the primary comparison.

For each filter f and timeframe t, the absolute net-profit difference is $\Delta NP(f,t) = NP(f,t) - NP(baseline,t)$. The profit-factor difference is $\Delta PF(f,t) = PF(f,t) - PF(baseline,t)$. Trade-count reduction is calculated as $100 \times [1 - Trades(f,t)/Trades(baseline,t)]$. These are descriptive comparisons; no statistical significance is implied by positive differences.

7. Results

7.1 Unfiltered baselines

Timeframe	Net profit	Profit factor	Trades	Commission	Max intrabar DD
1 minute	−$1,898,190.54	0.248	11,773	$1,851,930.88	$1,899,847.10
3 minutes	−$646,447.13	0.417	3,928	$619,524.82	$648,933.33
5 minutes	−$455,593.79	0.456	2,405	$378,731.43	$458,157.42
15 minutes	−$165,763.45	0.607	842	$132,382.39	$167,416.42
1 hour	$2,537.84	1.017	194	$30,739.63	$21,750.31

The unfiltered baseline is net-negative at 1-minute, 3-minute, 5-minute, and 15-minute timeframes. The 1-hour baseline is marginally positive at USD 2,537.84 with a profit factor of 1.017. Maximum intrabar drawdown is reported as a descriptive risk metric; initial capital is not used as a stop-out threshold or as a criterion for terminating or ranking these experiments.

7.2 Net profit and profit factor across filters

Filter	1m NP / PF	3m NP / PF	5m NP / PF	15m NP / PF	1h NP / PF
EMA	−$1,786,412.70 / 0.256	−$591,514.83 / 0.432	−$413,582.44 / 0.472	−$140,595.70 / 0.640	$7,476.50 / 1.057
EMA200	−$1,080,302.81 / 0.312	−$362,895.95 / 0.483	−$230,046.62 / 0.547	−$51,708.76 / 0.774	$144.79 / 1.001
Supertrend	−$1,832,885.49 / 0.253	−$587,466.22 / 0.435	−$385,594.80 / 0.491	−$103,478.17 / 0.709	−$1,776.96 / 0.988
MA Crossover	−$356,622.81 / 0.502	−$99,850.70 / 0.714	−$37,912.82 / 0.844	$17,550.33 / 1.155	$28,300.30 / 1.579
MACD Trend	−$1,503,754.46 / 0.283	−$509,029.82 / 0.458	−$365,298.00 / 0.493	−$99,987.15 / 0.710	−$1,812.45 / 0.986
ADX Trend	−$1,237,443.53 / 0.321	−$389,290.45 / 0.505	−$284,044.83 / 0.541	−$105,378.23 / 0.674	−$9,804.72 / 0.928
Renko HH-HL	−$1,879,582.59 / 0.248	−$603,560.96 / 0.433	−$435,676.12 / 0.463	−$141,005.36 / 0.645	$3,559.48 / 1.024

At 1-minute, 3-minute, and 5-minute timeframes, all seven filtered configurations remain net-negative and have profit factors below 1. At 15 minutes, MA Crossover is the only filtered configuration with positive closed-trade net profit (USD 17,550.33; PF 1.155). At 1 hour, EMA, MA Crossover, and Renko HH-HL are positive on closed-trade net profit, with PF values of 1.057, 1.579, and 1.024 respectively. These results are historical and subject to the data-integrity and robustness limitations described below.

7.3 Matched-baseline comparison

Timeframe	Filter	Δ net profit vs baseline	PF baseline → filter	Trades baseline → filter	Trade reduction
1 minute	EMA	$111,777.84	0.248 → 0.256	11,773 → 11,135	5.4%

1 minute	EMA200	$817,887.73	0.248 → 0.312	11,773 → 6,783	42.4%
1 minute	Supertrend	$65,305.05	0.248 → 0.253	11,773 → 11,365	3.5%
1 minute	MA Crossover	$1,541,567.73	0.248 → 0.502	11,773 → 2,130	81.9%
1 minute	MACD Trend	$394,436.08	0.248 → 0.283	11,773 → 9,313	20.9%
1 minute	ADX Trend	$660,747.01	0.248 → 0.321	11,773 → 7,873	33.1%
1 minute	Renko HH-HL	$18,607.95	0.248 → 0.248	11,773 → 11,611	1.4%
3 minutes	EMA	$54,932.30	0.417 → 0.432	3,928 → 3,688	6.1%
3 minutes	EMA200	$283,551.18	0.417 → 0.483	3,928 → 2,220	43.5%
3 minutes	Supertrend	$58,980.91	0.417 → 0.435	3,928 → 3,616	7.9%
3 minutes	MA Crossover	$546,596.43	0.417 → 0.714	3,928 → 686	82.5%
3 minutes	MACD Trend	$137,417.31	0.417 → 0.458	3,928 → 3,096	21.2%
3 minutes	ADX Trend	$257,156.68	0.417 → 0.505	3,928 → 2,446	37.7%
3 minutes	Renko HH-HL	$42,886.17	0.417 → 0.433	3,928 → 3,762	4.2%
5 minutes	EMA	$42,011.35	0.456 → 0.472	2,405 → 2,261	6.0%
5 minutes	EMA200	$225,547.17	0.456 → 0.547	2,405 → 1,309	45.6%
5 minutes	Supertrend	$69,998.99	0.456 → 0.491	2,405 → 2,114	12.1%
5 minutes	MA Crossover	$417,680.97	0.456 → 0.844	2,405 → 387	83.9%
5 minutes	MACD Trend	$90,295.79	0.456 → 0.493	2,405 → 1,914	20.4%
5 minutes	ADX Trend	$171,548.96	0.456 → 0.541	2,405 → 1,503	37.5%
5 minutes	Renko HH-HL	$19,917.67	0.456 → 0.463	2,405 → 2,295	4.6%
15 minutes	EMA	$25,167.75	0.607 → 0.640	842 → 775	8.0%
15 minutes	EMA200	$114,054.69	0.607 → 0.774	842 → 422	49.9%
15 minutes	Supertrend	$62,285.28	0.607 → 0.709	842 → 676	19.7%
15 minutes	MA Crossover	$183,313.78	0.607 → 1.155	842 → 128	84.8%
15 minutes	MACD Trend	$65,776.30	0.607 → 0.710	842 → 634	24.7%
15 minutes	ADX Trend	$60,385.22	0.607 → 0.674	842 → 530	37.1%
15 minutes	Renko HH-HL	$24,758.09	0.607 → 0.645	842 → 776	7.8%
1 hour	EMA	$4,938.66	1.017 → 1.057	194 → 172	11.3%
1 hour	EMA200	−$2,393.05	1.017 → 1.001	194 → 104	46.4%
1 hour	Supertrend	−$4,314.80	1.017 → 0.988	194 → 164	15.5%
1 hour	MA Crossover	$25,762.46	1.017 → 1.579	194 → 30	84.5%
1 hour	MACD Trend	−$4,350.29	1.017 → 0.986	194 → 146	24.7%
1 hour	ADX Trend	−$12,342.56	1.017 → 0.928	194 → 144	25.8%
1 hour	Renko HH-HL	$1,021.64	1.017 → 1.024	194 → 178	8.2%

MA Crossover shows the largest absolute net-profit improvement and the highest profit factor among the tested filters at each timeframe. Its trade-count reduction versus the unfiltered baseline is approximately 81.9% at 1 minute, 82.5% at 3 minutes, 83.9% at 5 minutes, 84.8% at 15 minutes, and 84.5% at 1 hour. This suggests that the crossover filter materially reduces trade frequency and cost exposure. However, improved performance relative to a poor baseline is not equivalent to profitability: the 1-, 3-, and 5-minute MA Crossover results remain negative.

7.4 Drawdown as a descriptive risk metric

Maximum intrabar drawdown is reported to describe the magnitude of adverse equity movement in each configuration. For MA Crossover, reported maximum intrabar drawdown is USD 358,622.30 at 1 minute, USD 100,889.34 at 3 minutes, USD 48,942.19 at 5 minutes, USD 23,486.23 at 15 minutes, and USD 20,572.60 at 1 hour. Initial capital is not treated as a stop-out threshold, backtest termination condition, or comparison criterion in this study. Drawdown remains relevant as a descriptive risk

metric, while any interpretation of its monetary magnitude depends on the instrument and execution assumptions.

7.5 Outlier-trade sensitivity

Timeframe	Configuration	Closed net profit	Flagged outlier count	Flagged outlier P&L
15 minutes	Unfiltered baseline	−$165,763.45	47	$122,285.04
15 minutes	EMA	−$140,595.70	29	$112,005.82
15 minutes	EMA200	−$51,708.76	16	$95,216.05
15 minutes	MA Crossover	$17,550.33	5	$63,002.78
15 minutes	Renko HH-HL	−$141,005.36	38	$128,095.43
1 hour	Unfiltered baseline	$2,537.84	3	$33,970.03
1 hour	EMA	$7,476.50	5	$48,412.64
1 hour	EMA200	$144.79	5	$64,568.33
1 hour	MA Crossover	$28,300.30	2	$36,451.54
1 hour	Renko HH-HL	$3,559.48	4	$38,792.35

For MA Crossover at 15 minutes, the workbook reports five outlier trades with aggregate outlier P&L of USD 63,002.78 against final net profit of USD 17,550.33. At 1 hour, it reports two outlier trades with aggregate outlier P&L of USD 36,451.54 against final net profit of USD 28,300.30. These figures warrant trade-level inspection. An exclusion sensitivity analysis should not be interpreted as a formal robustness test until the workbook's outlier definition and trade-level calculation are verified.

8. Discussion

My primary finding is that the moving-average crossover filter is associated with lower trade frequency and substantially improved historical results relative to the same-timeframe unfiltered baseline. The improvement appears across all five tested timeframes, but the filtered results remain net-negative on the 1-, 3-, and 5-minute charts. Positive closed-trade net profit is recorded for the moving-average crossover configuration at 15 minutes and 1 hour. In the 1-hour results, EMA and Renko HH-HL are also positive, although their profit factors are only marginally above 1. Taken together, these results suggest that the interaction between timeframe and directional confirmation matters for this strategy. One possible explanation is that short timeframes generate more frequent reversals and less persistent signals, increasing exposure to unsuccessful entries and transaction costs. However, I did not directly label individual signals as false breakouts or test whether each losing trade was caused by a reversal. I therefore treat this explanation as a hypothesis consistent with the observed pattern, rather than as a mechanism established by this experiment.

The 15-minute and 1-hour results require cautious interpretation. The 15-minute MA Crossover run is positive on closed-trade net profit but has a profit factor only modestly above 1 and is sensitive to a small set of flagged trades. The 1-hour MA Crossover run has the strongest reported profit factor but only 30 trades, a drawdown larger than initial capital, and outlier concentration. The positive 1-hour EMA and Renko HH-HL results are comparatively small, with profit factors close to 1. A single year of historical data and one instrument cannot establish that hourly or longer timeframes are generally superior, nor that the results will persist across market regimes. The present experiment tests only up to the 1-hour timeframe, so it cannot support a conclusion about timeframes longer than one hour.

The findings also highlight the importance of reporting transaction costs and drawdown alongside net profit. Commission expense is high in the higher-frequency configurations. A filter that reduces trading

frequency can improve net performance even when it does not make the strategy profitable. The paper should therefore emphasize comparative efficiency and limitations, rather than present the highest historical P&L as proof of a reliable trading system.

9. Next phase: prospective paper-trading validation

Future research could extend this historical comparison by first verifying the backtest settings and then conducting prospective forward testing of the leading filter configurations using live market data in paper-trading mode. Such testing would assess whether the observed reduction in trading frequency and relative performance improvement persist under incoming market conditions without deploying real capital. A paper-trading log could record timestamped signals, filter states, entries and exits, trade count, estimated commission and slippage, net simulated P&L, maximum drawdown, and manually or systematically classified false-breakout events. Researchers should define the testing duration, minimum trade count, and evaluation criteria before the test begins, and report the results regardless of whether they confirm the historical findings. Where feasible, the selected filtered configuration could be compared with its unfiltered baseline over the same forward period. Paper trading can help evaluate operational behaviour and signal persistence, but it does not fully reproduce live execution, market impact, liquidity constraints, or real-money trading psychology. No prospective paper-trading results are reported in the present study.

10. Limitations and validity threats

- Single BTCUSD instrument and one approximately one-year historical window limit generalizability.
- No untouched out-of-sample evaluation is documented.
- Forty configurations create a multiple-comparison and selection-bias risk; the best observed filter may be a result of chance or tuning.
- Reported drawdowns exceed the stated initial capital in several configurations; point value, contract sizing, margin, commission, slippage, and practical feasibility require verification before economic interpretation.
- Flagged outlier trades contribute substantially to positive results; the outlier definition and underlying trades need inspection.
- The exported results use reversal-based exits with fixed stop-loss, take-profit, and trailing-stop settings off. This is an exit policy, not a guarantee of a maximum loss.

 Prospective paper-trading forward testing is a recommended direction for future research; no such results are included in this manuscript.

11. Conclusion

This exploratory comparison evaluates seven technical filters against matched unfiltered Bollinger Band breakout-and-reversal baselines across five BTCUSD chart timeframes. The moving-average crossover filter produces the largest historical net-profit improvement and the highest profit factor among the tested filters at each timeframe, while reducing trade frequency by approximately 82–85%. Nevertheless, the lower-timeframe configurations remain net-negative at 1, 3, and 5 minutes. The moving-average crossover configuration is positive at 15 minutes and 1 hour, while EMA and Renko

HH-HL are also positive at 1 hour. This pattern is consistent with the hypothesis that directional confirmation may reduce exposure to unsuccessful short-horizon signals and the costs associated with frequent trading. However, the experiment did not separately identify false breakouts, and it does not establish that reversal frequency caused the observed losses. The positive 15-minute and 1-hour results also show drawdown and outlier sensitivity, and should not be treated as evidence of robust profitability. The principal contribution is a controlled, cost-aware historical comparison of trend filters across timeframes under a fixed reversal-based exit policy. A useful next stage for future research would be to take the leading filter configuration—particularly MA Crossover, subject to verification of the backtest assumptions—and evaluate it through live-market forward testing in paper-trading mode. This prospective phase will record signals, entries and exits, trade frequency, false-breakout classifications, transaction-cost assumptions, net results, and drawdown without risking real capital. I will define the evaluation period and acceptance criteria before testing, and compare the forward results with the historical findings. Further work should also verify the BTCUSD cost and point-value assumptions, inspect flagged outlier trades, directly classify false-breakout signals, and evaluate the leading configuration on an untouched chronological validation period. Until these checks are completed, conclusions should remain descriptive and exploratory.

The principal contribution of the study is a controlled, cost-aware comparison of filters across timeframes under a fixed reversal-based exit policy. Further work should reconcile source configuration and performance records, inspect flagged outlier trades, verify the BTCUSD cost and point-value assumptions, and evaluate the leading configurations on an untouched chronological validation period. Until then, conclusions should remain descriptive and exploratory.

Data Availability

The findings presented in this study are based on exported historical BTCUSD strategy-backtest workbooks generated using my proprietary Bollinger Breakout Engine v4.2. I have not made these workbooks publicly available because they contain confidential research materials and proprietary intellectual property, and I have not created a public repository for the underlying research data. I may consider providing non-confidential supporting information upon reasonable request, subject to intellectual-property protection and applicable restrictions. Any materials provided for editorial or peer-review purposes will be limited to materials that can be shared without disclosing proprietary source code or confidential trading logic.

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Additional information

Author Contributions. I developed the proprietary Bollinger Breakout Engine v4.2 strategy, designed the experimental framework, configured the tested parameters, conducted historical backtests, collected and organized the exported results, compared performance metrics, interpreted the findings, and prepared the manuscript. AI-assisted tools supported comparative interpretation and manuscript preparation. I am responsible for the accuracy of the reported results and the final content.

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Competing Interests. The author developed and owns the proprietary Bollinger Breakout Engine v4.2 strategy evaluated in this study. The strategy's source code and underlying trading logic constitute confidential intellectual property and are not publicly available. This ownership is disclosed for transparency. Other than this proprietary ownership, the author declares no competing interests.

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Declaration of AI-Assisted Analysis and Manuscript Preparation. I used ChatGPT (OpenAI) as an AI-assisted tool to help organize and compare exported backtest results and to assist with drafting and editing this manuscript. The tool did not replace my responsibility for research design, data verification, interpretation, or conclusions. I am responsible for checking all calculations, references, and statements before submission.

Research Status and Limitations. This manuscript reports exploratory historical backtest comparisons of a proprietary strategy applied to BTCUSD across five timeframes and seven technical trend filters. The study uses one approximately one-year historical period and 40 configurations, and no untouched out-of-sample evaluation is documented. Multiple-comparison risk, sensitivity to outlier trades, and the need to verify contract sizing and transaction-cost assumptions limit the conclusions. The results are not investment advice and do not establish guaranteed or future profitability.