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REVIEW

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Machine learning integration in cryptocurrency trading and its fintech implications

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Abstract
This review synthesises research on fintech implications of integrating machine learning algorithms into cryptocurrency trading strategies to address the fragmented understanding of their impact on trading efficacy, risk management, and financial innovation. The review aimed to evaluate current knowledge on machine learning applications, benchmark algorithmic trading performance, identify risk mitigation techniques, compare algorithm effectiveness, and examine regulatory and ethical considerations. A systematic analysis of diverse methodologies, including supervised, reinforcement, and hybrid learning models across global computational finance and AI literature, was conducted. Findings indicate that deep learning and ensemble methods significantly enhance predictive accuracy and trading profitability under volatile market conditions, while reinforcement learning frameworks improve dynamic portfolio optimisation and risk-adjusted returns. Risk management benefits arise from integrating technical indicators and reward-based safety mechanisms, though universal frameworks remain lacking. Fintech integration advances through blockchain-enabled transparency and automation, yet practical deployment faces scalability and interoperability challenges. Ethical and regulatory discourse is nascent, underscoring the need for responsible AI frameworks to ensure market integrity and investor protection. These findings collectively demonstrate that machine learning substantially transforms cryptocurrency trading strategies, offering enhanced performance and risk control within evolving fintech infrastructures, while highlighting critical gaps in regulatory compliance and ethical governance that warrant focused future research.

Keywords Cryptocurrency trading, Machine learning, Reinforcement learning, Fintech, Risk management, Systematic review

1 Introduction

Since the emergence of Bitcoin in 2008, cryptocurrency markets have evolved into a global financial ecosystem, characterised by extreme volatility, decentralisation, and technological innovation [1, 2]. These markets challenge traditional financial models due to their non-linear dynamics and speculative behaviour, making them an ideal environment for the application of machine learning (ML) techniques [3].

Discover

ML has increasingly been adopted in cryptocurrency trading for its ability to process vast amounts of data, identify patterns, and adapt to evolving market conditions. Techniques such as supervised learning, deep learning, and reinforcement learning (RL) offer promising alternatives to rule-based strategies [4, 5]. Among these, Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) have proven effective in time series forecasting, while ensemble models such as Random Forest and XGBoost demonstrate robustness against noise [6, 7].

Reinforcement learning approaches like Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) are particularly suited for trading applications due to their ability to model sequential decision-making and maximise cumulative returns [8]. Furthermore, hybrid models combining sentiment analysis with price prediction have gained attention, leveraging data from social media platforms to enhance prediction accuracy [9].

Despite these advances, several limitations remain. Overfitting, lack of interpretability, and insufficient generalisability are persistent technical concerns [10]. Ethical and regulatory challenges, such as algorithmic bias, data privacy, and market manipulation, also pose significant barriers to widespread adoption [11, 12].

This study aims to systematically evaluate the integration of ML into cryptocurrency trading from a fintech perspective. By analysing 57 peer-reviewed studies, we assess the effectiveness of various ML models, examine risk mitigation practices, and identify both opportunities and challenges in practical implementation. The goal is to provide a structured understanding of how ML contributes to performance optimisation, ethical automation, and technological transformation in crypto-financial systems.

Earlier review studies have mainly classified model architectures, prediction approaches, or feature-engineering techniques, and have examined machine learning methods largely from an algorithmic point of view. By contrast, this paper analyses the integration of machine learning into cryptocurrency trading through performance measures and fintech consequences. The literature is therefore organised along five analytical dimensions: (1) predictive performance, (2) trading performance, (3) algorithmic robustness, (4) risk management and volatility, and (5) fintech, market and regulatory implications. This framework allows a systematic assessment of the practical, strategic and market effects of machine learning models in cryptocurrency trading, moving beyond surveys that focus only on model design.

2 Methodology

This study follows a systematic literature review approach to examine the application of machine learning (ML) in cryptocurrency trading and its implications for fintech. The methodology was designed to ensure comprehensive coverage, transparency, and replicability, following recognised best practices in systematic research.

The aim of this review is not merely to summarise machine learning models used in cryptocurrency trading, but to compare supervised approaches that focus on predictive performance with reinforcement learning and portfolio-based models that optimise trading decision-making.

2.1 Research questions

The review is structured around the following five research questions (RQs):

- **RQ1**: How do supervised ML models improve predictive accuracy in cryptocurrency markets?
- **RQ2**: How do reinforcement learning and portfolio-based ML approaches improve trading performance in cryptocurrency markets?
- **RQ3**: What risk management techniques are facilitated by ML-driven trading strategies?
- **RQ4**: How are these algorithms integrated into fintech infrastructures and automated trading systems?
- **RQ5**: What ethical, regulatory, and practical limitations emerge in the use of ML for cryptocurrency trading?

These questions guided both the search strategy and the data synthesis stages.

Accordingly, the scope of the review is limited to ML applications in cryptocurrency trading environments.

2.2 Literature search and study selection

A comprehensive search strategy was applied across major academic databases, including Scopus, Web of Science, IEEE Xplore, SpringerLink, and arXiv. The initial query, *fintech implications of integrating ML in cryptocurrency trading*, was expanded into focused expressions such as:

- Reinforcement learning for portfolio optimisation in crypto markets.
- ML-based risk mitigation in crypto algorithmic trading.
- Sentiment analysis and price prediction in blockchain assets.

The search covered peer-reviewed articles and high-quality preprints published between 2016 and 2025, limited to English-language studies directly addressing cryptocurrency trading.

We also included selected preprints published on arXiv that demonstrated a high technical standard and reproducible methodology. These studies were essential for capturing the most recent trends and methodological advances, as research on cryptocurrency trading and machine learning evolves rapidly, with many relevant findings initially appearing in preprint form. Only those preprints were retained that provided detailed methodological descriptions, open-source code, or robust validation, ensuring that their scientific value was comparable to that of peer-reviewed publications.

Inclusion criteria:

- Studies applying supervised, unsupervised, deep, or reinforcement learning to cryptocurrency markets;
- Papers reporting empirical results on prediction, trading performance, or risk control;
- Articles discussing fintech-relevant elements such as automation, blockchain, or regulation.

Exclusion criteria:

- Studies on traditional finance only (e.g., stock or forex markets);
- Non-empirical works or those without reproducible methods;
- Duplicate or off-topic publications.

The inclusion and exclusion criteria were applied through a two-stage process.

In the first stage, we screened studies based on their title and abstract, excluding works that did not focus on cryptocurrency trading, did not apply machine learning methods for prediction or decision-making, or did not contain fintech-related implications.

In the second stage, we conducted full-text evaluation and retained only those studies that reported measurable trading performance, financial indicators, or risk-management outcomes. Only publications that met all of these criteria were included in the final sample.

The screening and selection process adhered to the PRISMA 2020 guidelines [13], ensuring transparent and systematic identification, screening, and reporting. Of the initial set of 282 articles, 57 were retained after title/abstract screening and full-text evaluation. Citation chaining (both backward and forward) was used to supplement the final sample (see Fig. 1).

The final set of articles was selected through a transparent screening pipeline using PRISMA principles, complemented by best practices in systematic data collection and visualisation [14].

The search strategy was intentionally directed toward a narrower thematic scope, namely the fintech implications of integrating machine learning into cryptocurrency trading strategies. Accordingly, broader studies addressing machine learning and

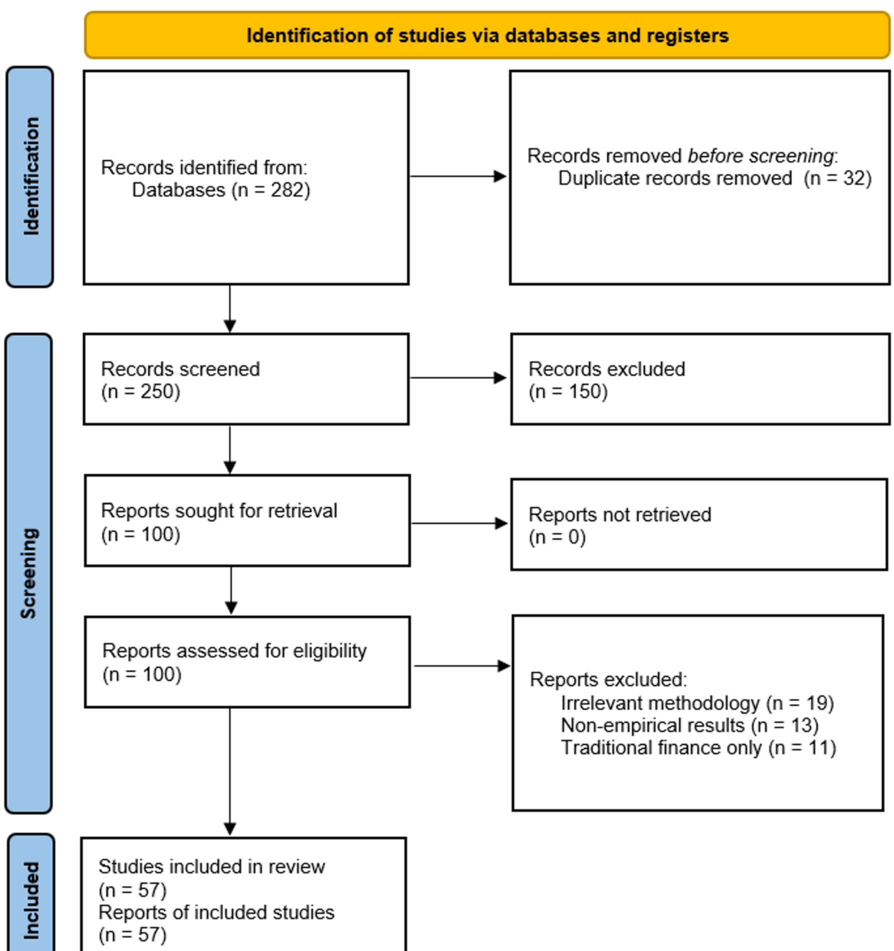

Fig. 1 PRISMA 2020 flow diagram for the study selection process. *Source Own editing based on* Page et al. [13]

cryptocurrencies in general (e.g., blockchain analytics, cryptocurrency mining, security, generic AI models, or analyses of the determinants of cryptocurrency price movements) were excluded already at the query level. This thematic focus explains why the initial PRISMA pool contained 282 relevant records rather than the several thousand results produced by broader keyword searches.The search terms intentionally excluded DeFi-specific mechanisms such as AMM-based pricing, liquidity provisioning, or smart-contract execution, as these environments require fundamentally different market assumptions and performance metrics. This review therefore focuses on machine learning applications in centralized cryptocurrency markets (CeFi), where trading is executed through orderbook-based mechanisms and standardized exchange protocols. Decentralized exchange environments (DeFi) fall outside the scope of this review.

2.3 Data extraction and thematic analysis

The selection of the five dimensions used for data extraction follows directly from the aims of this review, namely to examine the fintech implications of integrating machine learning into cryptocurrency trading strategies. These dimensions capture those relationships that make the models interpretable in terms of trading performance, risk-management approaches, technical and methodological characteristics, as well as fintech innovation and regulatory context. This framing is consistent with approaches used in the relevant literature, particularly in conceptual schemes applied to algorithmic trading, fintech systems, and the evaluation of machine learning models.

Data were extracted along five key dimensions:

1. **Model characteristics** algorithm type (e.g., LSTM, GRU, DQN), learning framework, optimisation goal;
2. **Performance metrics** accuracy, F1 score, RMSE, Sharpe ratio, ROI;
3. **Risk management methods** Value at Risk (VaR), stop-loss strategies, reward shaping;
4. **Computational aspects** latency, backtesting, scalability;
5. **Fintech integration** blockchain infrastructure, DeFi mechanisms, smart contracts, and regulatory concerns.

Thematic analysis was conducted using Braun and Clarke's [15] six-phase approach. This combined quantitative aggregation (e.g., number of studies using RL models) with qualitative coding (e.g., ethical implications, automation benefits).

Each study was mapped to one or more of the research questions. Summarised findings are presented in the Results section, while detailed tabular comparisons are provided in Appendix A to maintain clarity and conciseness in the main body of the paper.

3 Results

The studies reviewed in this paper reveal a number of methodological and thematic directions that shape the development of machine learning approaches in cryptocurrency trading. Particular emphasis is placed on models and techniques that directly influence trading decision-making, the learning of market patterns, and risk behaviour.

Greater attention is given to reinforcement learning models in portfolio management because these methods have become one of the most influential technical approaches in the domain of cryptocurrency trading. RL-based strategies are capable of continuously learning dynamic market conditions, adaptively adjusting positions, and modelling risk behaviour in an automated manner. This has a direct connection to the aim of the present study, which examines the fintech implications of integrating machine learning into trading strategies: the use of RL models represents a new level of automation, autonomous decision-making, and risk management.

3.1 Descriptive overview of reviewed ML-based crypto trading studies

This section maps the research landscape of the literature on fintech implications of integrating machine learning algorithms into cryptocurrency trading strategies, encompassing a broad spectrum of methodologies, including supervised learning, reinforcement learning, deep learning, and hybrid approaches. The studies predominantly focus on predictive modelling for price forecasting, trading strategy optimisation, and risk management within volatile cryptocurrency markets, often leveraging neural networks, decision trees, and reinforcement learning frameworks. Geographic and disciplinary diversity is evident, with contributions from computational finance, artificial intelligence, and ethical regulatory perspectives, reflecting the multifaceted nature of fintech innovation. This comparative analysis addresses key research questions by synthesising empirical findings on algorithmic performance, risk mitigation, and the broader fintech ecosystem impacts, including ethical and regulatory considerations.

To provide a comprehensive view of the literature, the following part of this subsection presents a thematic analysis structured around five key domains identified during the review: predictive accuracy, trading performance, risk management effectiveness, algorithmic efficiency, and fintech integration impact. This classification reflects the dominant methodological and conceptual trends observed across the selected articles.

The analysis does not categorise the reviewed literature by algorithmic models or architectural types, but rather according to performance metrics and application contexts.

A detailed summary of all 57 reviewed studies, including key characteristics, applied machine learning techniques, and major findings, is presented in Appendix A. The appendix table follows the same five analytical dimensions used in the main text, ensuring transparency and reproducibility of the review. This structured analytical framework allows machine learning models to be evaluated not solely on their predictive accuracy, but on their influence on trading decisions, risk dynamics, and their broader impact on the financial ecosystem.

3.1.1 Predictive accuracy

Numerous studies (n = 40) reported that deep learning architectures such as LSTM and GRU offer substantial improvements in prediction accuracy over traditional models [16–18]. Ensemble methods and reinforcement learning strategies further enhance robustness across different market regimes [19–21]. Moreover, integrating sentiment analysis from social media and causal feature engineering boosts performance [22–24].

3.1.2 Trading performance

A total of 38 studies indicated that ML-based trading strategies outperformed traditional benchmarks like buy-and-hold, especially in terms of Sharpe ratio, return consistency, and drawdown reduction [25–27]. Reinforcement learning models with novel reward structures yielded notable adaptability and profitability [28–30]. Some researchers focused on portfolio optimisation and risk-adjusted return frameworks [31–33].

3.1.3 Risk management effectiveness

Thirty studies incorporated financial risk metrics, such as Value at Risk (VaR), drawdown controls, and the Sharpe Ratio, to evaluate and mitigate model-induced risks [20, 34, 35]. Hybrid architectures using technical indicators in conjunction with ML methods enhanced the detection of market anomalies and reduced false trading signals [36, 37]. Reinforcement learning models featuring penalty mechanisms and conservative position sizing demonstrated prudent risk-reward trade-offs [22, 38].

3.1.4 Algorithmic efficiency

Approximately 25 studies dealt with the practical implementation of ML models, focusing on scalability, real-time performance, and computational efficiency. Genetic algorithms and hyperparameter optimisation techniques were deployed to reduce overhead and improve performance [16, 39, 40]. Deep reinforcement learning with attention mechanisms proved effective in multi-asset scenarios and long sequence processing [41].

3.1.5 Fintech integration impact

Around 20 studies tackled the broader fintech implications of ML integration. Key themes included regulatory compliance, explainability, fairness, and AI governance in crypto-finance ecosystems [42–44]. The convergence of AI and blockchain improved system transparency, fraud detection, and investor trust [45, 46]. Despite these gains, the literature identified a need for consistent ethical and regulatory frameworks to ensure responsible deployment [47].

3.2 Temporal trends in ML applications for cryptocurrency trading

Most of the reviewed studies implement cryptocurrency trading models in environments that aim to reproduce actual market conditions. In this paper, the term “real-world trading environment” refers to systems based on historical market data or simulated trading using exchange APIs. These settings model market processes in a manner that approximates real behaviour, but they do not involve actual capital allocation or live execution of transactions. Implementations in genuine live trading environments are rare in the examined literature and require substantially different technical, financial and risk-management conditions in practice.

The integration of machine learning into cryptocurrency trading strategies has evolved considerably from 2016 onwards, reflecting increasing sophistication in modelling techniques and expanding fintech implications. Early research primarily focused on applying basic machine learning models to price prediction and algorithmic trading in cryptocurrencies. Over time, studies incorporated deep learning and reinforcement learning to tackle market volatility and enhance decision-making in automated trading systems. Recent advancements emphasise hybrid models, sentiment analysis, ethical considerations, and the development of robust frameworks to optimize trading performance while addressing regulatory and operational challenges in the dynamic cryptocurrency market. A structured summary of the temporal evolution of ML applications in

Table 1 Chronological evolution of ML applications in cryptocurrency trading (2016–2025). *Source* Author's own editing based on reviewed articles

Years	Research direction	Key development
2016–2018	Early ML in crypto trading	Sentiment-data integration and basic supervised prediction models
2019–2020	Deep RL & portfolio frameworks	Shift toward decision-making and dynamic risk handling
2021–2022	Hybrid DL architectures	Combining market indicators with social/sentiment inputs
2023	Ethical & regulatory fintech layering	Transparency, explainability, compliance considerations
2024	Optimization &	Cross-crypto model adaptation and profitability focus
2025	Real-time trading systems	Adaptive ML deployment in exchange-like environments

Table 2 Dominant research themes in ML-based cryptocurrency trading ($n = 57$ papers). *Source* Author's own editing based on reviewed articles

Theme	Core focus	ML contribution
Price prediction & trading performance	Short-term forecasting of market movements	Improves entry/exit timing and profit optimisation
Reinforcement learning & portfolio strategies	Adaptive decision-making and dynamic allocation	Learns trading policies and adjusts exposure based on reward
Risk management & volatility mitigation	Drawdown control and uncertainty reduction	Detects unstable regimes and stabilises trading performance
Sentiment & external data integration	Social media, news, and macro signals	Enhances prediction beyond pure market indicators
Ethical, regulatory & fintech implications	Transparency, responsibility, compliance	Frames ML deployment within real-world financial systems

cryptocurrency trading is provided in Table 1. The extended descriptions and contextual examples are available in Appendix B.

3.3 Thematic insights into ML strategies and fintech integration

Several recurring thematic directions emerge in the literature on machine learning approaches applied to cryptocurrency trading. These thematic groups reflect the intended use and methodological focus of different model families, such as price forecasting, decision support, portfolio management, sentiment analysis, and the handling of operational or governance environments. The main thematic directions are summarised in Table 2.

The study-level examples and implementation variants associated with each thematic direction are documented in Appendix C, which serves to ensure transparency and reproducibility.

3.4 Cross-study evaluation of methodologies and fintech implications

The reviewed studies reveal recurring advantages and limitations across machine learning approaches applied to cryptocurrency trading. These aspects range from methodological flexibility and algorithmic performance to challenges related to robustness, overfitting, and execution in real trading environments. A high-level comparison of these strengths and weaknesses is summarised in Table 3.

The extended version of this comparative matrix, including study-level examples, performance indicators, and methodological notes, is documented in Appendix D.

To enhance the clarity of the comparative findings, a visual summary is provided in Fig. 2.

Table 3 High-level comparison of strengths and weaknesses across ML approaches in cryptocurrency trading. *Source* Author's own editing based on reviewed articles

Aspect	Strengths	Weaknesses
Methodology	Broad range of ML techniques enables flexible modelling across different market regimes.	Limited consistency in experimental design and evaluation protocols.
Algorithmic performance	ML methods can outperform baseline and heuristic approaches in short-term prediction tasks.	Results often lack robustness and generalizability across assets.
Risk management	RL and portfolio models adaptively adjust exposures and mitigate drawdowns.	Liquidity, slippage and execution-related constraints are rarely addressed.
Fintech integration	ML approaches support automation and scalable trading workflows.	Deployment is hindered by institutional constraints and infrastructure limitations.
Ethical & regulatory	AI governance frameworks encourage transparency and accountability.	Lack of regulation, model explainability and operational standards slows adoption.

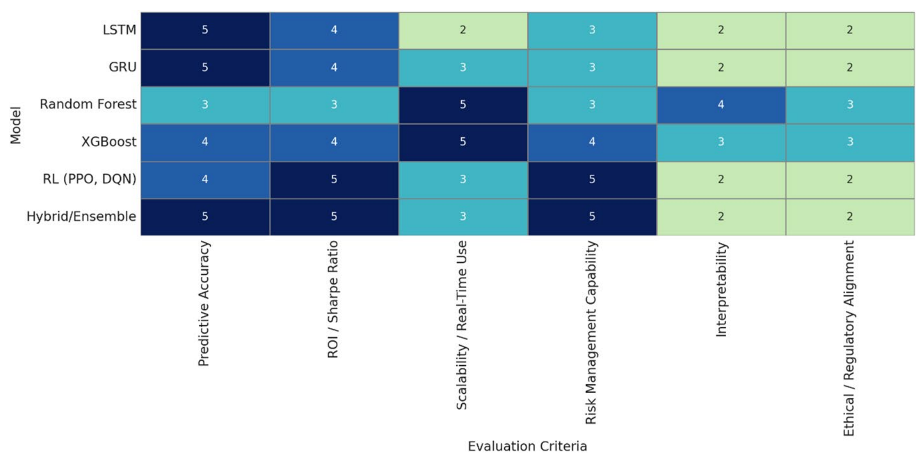

Fig. 2 Visual comparison of machine learning models used in cryptocurrency trading based on six key evaluation criteria (1–5 scale). *Source Authors' compilation based on reviewed articles*

The heatmap highlights the relative strengths and limitations of key machine learning models based on six evaluation criteria: predictive accuracy, return on investment, scalability, risk management capability, interpretability, and regulatory alignment.

The numerical ratings (on a 1–5 scale) are derived from the authors' synthesis of the reviewed literature and represent a qualitative aggregation of model characteristics discussed in Sect. 3.1 to 3.4.

This visualisation complements Table 3 and supports readers in quickly identifying which models are most suitable under specific constraints and objectives.

As shown in Fig. 2, deep learning models such as LSTM and GRU demonstrate high predictive accuracy and solid ROI, but they generally lack interpretability and scalability. In contrast, traditional ensemble methods like Random Forest and XGBoost offer better scalability and interpretability, though at the cost of slightly lower predictive performance.

Reinforcement learning (RL) techniques appear particularly effective in risk-sensitive environments, achieving high ROI and strong risk management capabilities, albeit with limitations in real-time scalability.

Hybrid and ensemble models generally offer a balanced trade-off across most dimensions, but their complexity may hinder deployment in resource-constrained environments.

These distinctions underscore the importance of aligning model choice with specific application goals, for example, using RL models in highly dynamic and volatile markets, whereas Random Forest may be more appropriate when interpretability and compliance requirements are prioritised.

3.5 Theoretical and practical implications

To bridge the gap between academic inquiry and real-world application, this section synthesises the theoretical contributions and practical implications of integrating machine learning (ML) into cryptocurrency trading. The reviewed literature indicates how advanced computational models not only reshape predictive finance theory but also provide actionable insights for traders, fintech developers, and policymakers.

3.5.1 Theoretical implications

- The integration of machine learning algorithms into cryptocurrency trading strategies substantiates the hypothesis that ML can significantly enhance predictive accuracy and trading profitability. These findings support the view that advanced computational models outperform traditional financial models in volatile markets, thus challenging classical efficient market hypotheses by revealing exploitable inefficiencies in cryptocurrency markets [4, 16, 21].
- Reinforcement learning (RL) and deep learning models, particularly those employing hybrid and multi-agent frameworks, contribute to theoretical developments by addressing dynamic market conditions and risk management. Their adaptability and robustness in non-stationary environments expand the theory of algorithmic trading under uncertainty [25, 28, 38].
- The incorporation of sentiment analysis and social media data into ML-based forecasting introduces a behavioural dimension to price prediction theories. This highlights the influence of investor sentiment and informational flows on cryptocurrency price dynamics, bridging finance, behavioural economics, and data science [23, 24, 48].
- Ethical and regulatory aspects arising from AI-driven trading challenge conventional frameworks of market efficiency and fairness. These findings suggest the need for expanded models that integrate the normative and institutional consequences of algorithmic decision-making in financial markets [42, 46, 47].
- Comparative evaluations of ML algorithms indicate that ensemble and deep learning approaches, such as gradient boosting and LSTM networks, excel at capturing short- and long-term temporal dependencies in highly volatile price series. These insights refine theoretical models of time series forecasting and financial prediction [4, 19, 49].

3.5.2 Practical implications

- The consistent outperformance and robustness of ML-based trading strategies suggest considerable potential for fintech firms and individual traders to optimise portfolio management and risk mitigation. The findings support the broader application of AI-powered tools for real-time decision-making in digital asset markets [21, 26, 30].
- Seamless integration of ML models with blockchain infrastructure—such as smart contracts and oracles—offers practical pathways to transparent, decentralised, and automated trading systems. These innovations lower participation barriers and contribute to financial inclusion [26, 44, 46].
- The identified ethical and regulatory challenges call for the development of governance frameworks and compliance mechanisms specifically tailored to AI-driven cryptocurrency trading. Addressing algorithmic biases, fraud prevention, and regulatory transparency is vital for ensuring sustainable fintech innovation [42, 47].
- Reinforcement learning and multi-agent systems demonstrate practical utility in dynamic asset al.location and volatility management. Their ability to adapt to changing market regimes presents a valuable toolset for building resilient trading systems [28, 35, 38].
- The use of sentiment analysis and alternative data sources in ML pipelines significantly enhances predictive capabilities. These findings suggest that fintech applications should integrate multimodal data to improve market forecasts and trading signal reliability [23, 24, 50].
- Despite the promising outcomes, issues such as limited model generalisability, sensitivity to extreme market shocks, and unaccounted transaction costs remain critical concerns. This underscores the need for continuous empirical validation and iterative model development to ensure scalability and operational viability in real-world trading environments [4, 20, 21].

4 Discussion

This section critically interprets the reviewed literature in relation to the study's core research questions and thematic domains. The aim is to provide a structured reflection on how the integration of machine learning (ML) into cryptocurrency trading strategies has influenced predictive performance, risk mitigation, fintech integration, and regulatory preparedness.

4.1 Predictive modelling of supervised models

The performance of supervised models in cryptocurrency markets is typically expressed through their ability to forecast price movements. LSTM and GRU architectures are frequently reported to outperform linear benchmarks and shallow neural networks, as they can capture non-linear and long-range temporal dependencies in market data. Several studies show that these models achieve lower forecast errors, although they are sensitive to volatility shocks and regime changes. When market conditions shift rapidly, ensemble methods such as Random Forest or Gradient Boosting are often more stable, as they tend to react less erratically to noisy and heterogeneous inputs.

Model performance is therefore context dependent. During bullish periods, deep learning models commonly achieve higher directional accuracy. In contrast, during sideways or uncertain regimes, ensemble structures often operate within smaller error bands. Hybrid designs, such as CNN-LSTM models, offer a middle ground: they provide moderately improved short-term forecasting while maintaining greater resilience in turbulent conditions. However, these approaches require more complex parameter tuning and larger datasets.

These findings do not suggest a linear ranking of methods but rather conditional advantages:

- Deep learning performs strongly in trend-stable environments,
- Ensemble methods are generally more robust in periods of market noise or regime shifts,
- Hybrid architectures bridge the two, albeit at higher data and resource costs.

This directly relates to RQ1, as it shows that supervised models do not deliver universally superior predictive performance; instead, their effectiveness is optimised for specific market environments.

4.2 Trading performance of reinforcement and portfolio-based models

Models that focus on trading decision-making, including portfolio optimisation strategies and rule-based allocation frameworks, do not aim to increase the accuracy of price forecasts. Instead, they optimise the financial outcome of market operations. In these approaches, decision-making is represented through a reward function: the model does not learn what the future price will be, but which action, such as taking a long or short position, reallocating capital, or adjusting portfolio weights, maximises total return or reduces risk in a given market state.

These methods do not perform uniformly across environments. Portfolio-based strategies often show strong results in periods of high volatility, as dynamic rebalancing can reduce exposure during turbulent conditions. Their performance declines, however, when transaction costs are substantial or liquidity is limited, since frequent adjustments amplify slippage and fee accumulation. Several studies indicate that buy-and-hold or simple momentum strategies outperform dynamic approaches when trading costs penalise frequent reallocation.

The performance of decision-optimising models therefore derives not from predictive accuracy but from the efficiency with which they manage risk-return trade-offs, respond to market states, and operate under cost and liquidity constraints. As a result, a model that delivers a high Sharpe ratio in liquid, low-cost settings may underperform in markets characterised by wide spreads or frequent regime shifts. In many cases, these contextual effects influence outcomes more strongly than differences in model architecture.

This directly addresses RQ2, demonstrating that improvements in trading performance arise from optimising decision rules rather than from more accurate forecasting of price movements.

4.3 Algorithmic robustness and adaptability

The robustness and adaptability of machine learning models are critical in cryptocurrency trading, where markets are not only volatile but also structurally dynamic. For supervised models, robustness is often tied to data volume and training duration. Deep neural networks tend to improve when longer historical sequences are available, yet several studies report overfitting and regime-dependent behaviour, particularly when prices follow a local trend and subsequently reverse. In contrast, ensemble methods such as Random Forest or Gradient Boosting are less sensitive to temporal breakpoints, but they generally fail to capture persistent trend structures, which can lead to underperformance during extended bullish phases.

In models that optimise decision-making logic, robustness appears in a different dimension. Dynamic portfolio allocation and reward-based decision rules react quickly to market noise and can substantially reduce exposure during extreme events. However, this adaptability introduces stochastic behaviour, which can severely weaken overall trading outcomes when transaction costs are high or liquidity is constrained. Hybrid approaches, including CNN-LSTM models combined with portfolio strategies, appear in some studies to compensate for model sensitivity, though they require complex parameter calibration and large historical datasets to remain stable.

Algorithmic robustness in cryptocurrency markets therefore stems not from inherent model "quality" but from alignment with the surrounding environment. Two contrasting patterns emerge in the literature. Some studies show that deep networks consistently perform better when trained on a single, well-defined regime. Others find that hybrid or ensemble approaches suffer smaller performance losses during market breaks, geopolitical disruptions, regulatory announcements, or liquidity shocks. These results indicate that robustness in ML-based trading cannot be reduced to generalisation ability alone, but should instead be understood through model behaviour under stress regimes. Models that remain stable during transitional turbulence often perform worse during prolonged trend phases, and vice versa, which forces strategic trade-offs when designing trading systems.

4.4 Risk management and volatility handling

One of the most critical characteristics of cryptocurrency markets is volatility clustering, which produces heavy-tailed return distributions and non-linear price dynamics. In supervised models, volatility is handled implicitly through temporal patterns in the data, and performance tends to depend on the market regime experienced during training. This approach performs well during bullish or stable periods; however, most studies report sharp performance degradation during regime shifts, macroeconomic shocks or panic events. Forecasting errors increase non-linearly, and model behaviour that appears stable under normal conditions often performs weakest precisely when returns are most extreme.

Portfolio-based approaches or reward-driven models employ a different risk-management mechanism. These methods use explicit exposure reduction, reweighting rules or risk-sensitive decision logic. They are able to respond rapidly when volatility rises, and many studies show that they mitigate negative returns and reduce drawdowns during turbulent phases. This adaptability comes at a cost: frequent rebalancing introduces transaction fees, slippage and liquidity losses, which often partially or completely absorb the apparent gains of the model.

These contradictions are particularly visible in studies comparing active exposure reduction with passive benchmark tracking. Risk-sensitive portfolio models deliver more predictable outcomes in turbulent conditions, yet many works show that this "defensive posture" leads to underperformance in the early stages of bull markets, as exposure increases too late and a large share of returns remains unrealised. Prediction-based approaches tend to identify strengthening signals earlier, but collapse when the signal is false or short-lived.

Machine learning models used in cryptocurrency trading therefore do not differ in how well they "manage volatility," but rather in how and at which phase they react to it:

- Supervised models treat volatility as noise, seeking stable predictive patterns that hold only in certain market regimes.
- Portfolio- or reward-based models treat volatility as a signal, prompting exposure reduction or structural reallocation.

In practice, these trade-offs are the most consequential. Prediction-driven models accumulate risk over time, while volatility-responsive models accumulate transaction costs. The literature provides no clear winner: the effectiveness of risk management depends on the temporal structure of the market environment and the underlying cost conditions, not on the category of the model itself. These patterns directly relate to RQ3, as risk mitigation in cryptocurrency trading emerges not from model architecture but from the model's behavioural response to volatility phases.

4.5 Fintech integration and technical feasibility

The practical integration of machine learning models in cryptocurrency trading depends less on their theoretical accuracy and more on their ability to operate within fintech execution infrastructures. Supervised models are typically developed offline and then linked to a separate trading layer. This architecture introduces structural delays: the interval between the generation of a prediction and its execution can eliminate part of the market patterns the model originally detected. In contrast, decision-oriented approaches based on reinforcement learning treat trading as a sequential decision problem, selecting actions directly rather than providing a forecast. These systems, however, must function in real-time environments, where API rate limits, quoting depth, order execution latency and slippage continuously reshape model behaviour.

The divergence between simulated results and operational outcomes appears as a deployment gap. Several studies report strong back-tested performance that cannot be reproduced in live execution environments, or where a substantial share of expected returns is eroded by trading fees, liquidity frictions or market impact. The effect is particularly visible in high-frequency conditions, where order book dynamics and microstructure behaviour can override the logic of the algorithm. Laboratory settings, in which models behave as if decisions were frictionless optimisations, do not capture these constraints.

Integration is therefore not a purely technical exercise but a matter of financial innovation. Automated decision-making alters execution pathways, liquidity allocation patterns and the temporal structure of position building. These changes affect how trading infrastructures behave at the operational level. Model architecture alone rarely explains trading performance; results are shaped by the execution system into which the algorithm is embedded and by the extent of autonomy delegated to the model relative to human oversight.

Hybrid implementations illustrate this principle. Systems in which trading decisions are algorithmic, but order execution is regulated or monitored, often produce more stable outcomes than frameworks where the entire trading process is delegated to the model. Technical feasibility is not binary. Machine learning systems are not simply “deployable or not deployable”; their viability scales with the capabilities and constraints of the execution layer. As a consequence, deployed strategies often reflect adaptation to their environment rather than a direct projection of theoretical optimum.

These considerations directly address RQ4. The performance of machine learning in cryptocurrency trading does not stem solely from predictive ability or a model’s internal decision logic. It depends on which layers of the trading process are automated, how they are integrated into fintech infrastructure, and how market microstructure, API constraints and transaction costs reshape the model’s behaviour. Evaluating architectures without considering deployment conditions leads to incomplete and potentially misleading conclusions about practical feasibility.

4.6 Ethical, regulatory, and operational considerations

The risks associated with ML-based cryptocurrency trading extend beyond financial losses. Models trained on historical data inherit past market distortions such as manipulated cycles, liquidity shocks or speculative phases. These biases are embedded in the decision space and may produce trading behaviour that appears reliable in controlled tests but leads to excessive exposure in live environments. Reinforcement learning and reward-optimising portfolio models are particularly vulnerable, as they may favour short-term returns over long-term stability.

Opacity further intensifies these risks. The decision logic of complex models cannot be reduced to human-readable rules, which complicates accountability and auditability. Responsible AI practices address this challenge by increasing decision transparency, for example through SHAP or LIME, which link model outputs to specific features or market conditions. This traceability is essential for compliance and investor protection.

Fairness in this domain refers to trading opportunity fairness. Biased models may repeatedly favour certain trading patterns or instruments, disadvantaging other market participants, especially in low-liquidity environments or where pricing can be influenced. Such imbalances can amplify structural market inequalities.

Regulatory frameworks impose additional constraints. MiCA, SEC and ESMA guidelines emphasise transparency of decision processes, risk-limit enforcement and investor-protection standards. Although primarily oriented toward centralised intermediaries, these requirements indirectly apply to ML systems, as they demand clear responsibility, auditability and risk control.

Finally, most studies assess algorithms in idealised conditions, while real markets impose latency, API limits, order book depth, minimum transaction sizes and layered fees. These frictions often erode theoretical returns and produce behaviour that diverges substantially from back-tested results. As automation increases, systemic risks intensify and corrective intervention becomes more difficult.

These constraints address RQ5, as the applicability of ML models in cryptocurrency trading depends not only on performance, but also on the interpretability of their decisions, the equitable distribution of trading opportunities and the ability to meet evolving supervisory and infrastructural requirements.

5 Conclusion

This systematic review examined the fintech implications of integrating machine learning (ML) algorithms into cryptocurrency trading strategies, analysing 57 peer-reviewed studies across five core domains: predictive performance, algorithmic trading optimisation, risk management, technological integration, and ethical–regulatory challenges.

With regard to RQ1 (How do supervised ML models improve predictive accuracy in cryptocurrency markets?), the evidence supports that ML algorithms, particularly deep learning architectures such as LSTM and GRU, can significantly enhance predictive accuracy and short-term trading outcomes [16, 18, 21]. These models outperform statistical benchmarks across a range of assets and time horizons, especially in stable or moderately volatile regimes. However, their performance deteriorates during structural breaks, liquidity shocks or regime shifts, indicating that predictive gains are conditional and not universally generalisable.

Concerning RQ2 (How do reinforcement learning and portfolio-based ML approaches improve trading performance?), the review found strong empirical support for reinforcement learning (RL) and hybrid models in dynamic market environments. Actor-critic frameworks and multi-agent systems demonstrate superior adaptability, risk-return profiles and rebalancing capabilities in volatile markets [25, 28]. These advantages do not originate from forecast accuracy but from end-to-end decision logic, reward shaping and sequential optimisation.

Addressing RQ3 (What risk management techniques are facilitated by ML-driven trading strategies?), several studies show that ML models improve the handling of short-term volatility and false signals, especially when combined with hybrid indicators or risk-adjusted metrics such as the Sharpe Ratio and Value-at-Risk [35, 37]. Nonetheless, comprehensive frameworks for tail-risk, leverage-induced fragility, liquidity stress and black-swan events remain underdeveloped.

Findings related to RQ4 (How are these algorithms integrated into fintech infrastructures and automated trading systems?) were mixed. While numerous papers propose ML-driven trading platforms using blockchain components, API-based automation or smart-contract execution [26, 46], real-world deployment remains limited. Practical constraints—including scalability, latency, execution delays, fee stacking, and interoperability, restrict the feasibility of large-scale adoption and materially affect realised performance.

Finally, RQ5 (What ethical, regulatory, and practical limitations emerge in the use of ML for cryptocurrency trading?) remains insufficiently resolved. Although recent contributions emphasise explainability, fairness, model auditability, and investor protection [43, 47], operational and legal frameworks for responsible ML use are still in their early stages. The rapid pace of AI-driven trading currently exceeds the maturity of governance systems designed to regulate it.

In conclusion, the integration of ML into cryptocurrency trading demonstrates meaningful progress in predictive analytics, adaptive strategy design and volatility management. Yet these benefits are context-dependent, shaped by market microstructure, regulatory constraints and infrastructural limitations. Future research should prioritise the development of robust, interpretable and regulation-aligned ML systems that operate reliably under live trading conditions and contribute to market integrity, investor protection and sustainable financial innovation.

6 Limitations

Although this review provides a broad overview of machine learning applications in cryptocurrency trading, several limitations should be acknowledged. First, the analysis is limited to peer-reviewed studies published in English between 2016 and 2025. This publication and language bias may exclude relevant perspectives from industry reports, non-English research communities or regional fintech ecosystems, particularly in Asia and Latin America, where digital asset innovation often precedes academic documentation. As a result, the findings should not be interpreted as globally exhaustive.

Second, the review's thematic scope focuses on ML integration within technical trading frameworks, addressing predictive performance, reinforcement learning, portfolio optimisation, and fintech implications. This focus does not consider behavioural finance, institutional adoption barriers, taxation or legal-economic perspectives on algorithmic execution. Additionally, most reviewed studies rely on historical backtesting or simulated trading environments. While these methods provide valuable methodological insight, they do not necessarily reflect operational constraints such as latency, fee stacking, market depth, slippage, and risk of liquidity cascades. Consequently, the reported performance gains should be interpreted as conditional rather than universally deployable.

From a methodological standpoint, ML-specific limitations persist across the literature. Many studies lack transparency regarding hyperparameter tuning, validation protocols, or data leakage prevention, which increases the risk of overfitting and artificially inflated performance. Moreover, in supervised models, predictive accuracy does not automatically translate into profitable strategies, whereas reinforcement learning approaches may overfit reward functions or exhibit unstable behaviour in regime shifts. These problems directly affect the scope of RQ1 and RQ2, highlighting the gap between theoretical effectiveness and practical robustness.

Another concern is publication bias: positive or high-performance results are substantially more likely to be published than negative or inconclusive findings. This may skew the perception of ML model effectiveness and lead to overly optimistic interpretations of their real-world viability. In addition, most studies do not report failed deployments, parameter instabilities or capital drawdowns larger than the benchmark, issues crucial for institutional adoption. Looking forward, future research should prioritise empirical validation under live market conditions and examine how execution-layer constraints, API rate limits, partial fills, liquidity fragmentation, affect realised outcomes. A related priority is the integration of explainable AI (XAI) and responsible AI principles into ML-driven trading systems to enhance interpretability, auditability and regulatory compliance. This relates directly to RQ4 and RQ5.

Promising directions include multimodal data fusion—combining on-chain analytics, macroeconomic indicators and real-time sentiment signals—together with stress-testing models under extreme volatility and black-swan events. Furthermore, the intersection between machine learning and decentralised finance warrants deeper exploration: autonomous liquidity provision, smart-contract execution and AMM price discovery introduce new risk surfaces and transparency patterns distinct from CeFi infrastructures.

By addressing these limitations and expanding the methodological and fintech horizons, future research can better navigate the interplay between artificial intelligence, market infrastructure, and digital asset regulation.

Supplementary Information

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Supplementary Material 1.

Author contributions

P.L. conceived the study, developed the methodological framework, coordinated the research process, and contributed to the manuscript writing. J.P. performed the literature review, data analysis, and prepared the comparative tables. I.F. contributed to the interpretation of results and manuscript revision. All authors reviewed and approved the final manuscript.

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Data availability

The study is based on publicly available academic literature and does not rely on proprietary or primary datasets. A full list of reviewed studies is included in Appendix A. Any additional materials or coding frameworks used in the thematic synthesis are available from the authors upon reasonable request.

Declarations

Ethics approval and consent to participate

This study is a systematic literature review and did not involve human participants, clinical data, or experiments requiring ethical approval. Therefore, ethical approval was not required. No human participants were involved in the research; therefore, consent to participate was not applicable.

Consent for publication

The manuscript contains no identifiable personal data, proprietary datasets, or sensitive information. All included data are derived from publicly accessible academic sources. Therefore, consent to publish is not applicable.

Competing interests

The authors declare no competing interests.

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