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Uniswap V4 Concentrated Liquidity Pricing: a Machine Learning Model for U.S. Institutional Liquidity Providers

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Abstract: Amid the institutionalization wave of Decentralized Finance (DeFi), U.S. institutional Liquidity Providers (LPs) have emerged as the core incremental capital for leading Decentralized Exchanges (DEXs). However, the adaptation gap between Uniswap V4's concentrated liquidity mechanism and institutional risk preferences, as well as regulatory compliance requirements, has hindered their market entry. This study focuses on the integration of "technical characteristics - institutional constraints - precise pricing" and constructs a machine learning pricing model optimized across three dimensions: return, risk, and compliance. By integrating Uniswap V4 on-chain data, institutional risk preference data, and market data, a Stacking ensemble architecture combining LightGBM and CNN-LSTM is designed, incorporating 22 core features to achieve precise pricing. Empirical results show that the model's Mean Absolute Error (MAE) on the test set was reduced by 37% compared to the benchmark, and the Root Mean Square Error (RMSE) is reduced by 42%. The Sharpe ratio reaches 1.87 (an increase of 62% compared to the benchmark), with a volatility of 15.3% and a compliance adaptability score of 91. In the case study, a $150 million liquidity supply achieved a 19.7% annualized return and an 8.3% maximum drawdown, successfully passing SEC compliance review. This research fills the gap in institution-oriented pricing models for V4, improves the institutional extension of Automated Market Maker (AMM) pricing theory, and provides a risk-controllable and compliance-adaptable pricing tool for U.S. institutions participating in DeFi, promoting the transformation of the DeFi ecosystem towards standardization and institutionalization. By aligning the V4 Hook mechanism with U.S. regulatory frameworks, this research provides a scalable technical standard for institutional DeFi adoption, reinforcing the competitive advantage of the U.S. Web 3 financial ecosystem.

Keywords: Uniswap V4, Machine Learning, U.S. Institutional LPs, DeFi Institutionalization, Risk Management, Stacking Ensemble Learning.

Disciplines: Computer Science. **Subjects:** Machine Learning Model.

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1 INTRODUCTION

1.1 RESEARCH BACKGROUND AND PRACTICAL DRIVERS

The DeFi liquidity mechanism has evolved from basic adaptation to precise optimization. Uniswap V2's constant product model laid the foundation for automated market making, but its single fee structure and global liquidity allocation struggled to match asset volatility characteristics. [1]V4 achieved a breakthrough through concentrated liquidity, dynamic fees, and the hook mechanism, allowing LPs to lock assets within specific price ranges and embed custom logic such as slippage protection and stop-loss triggers. This has driven Uniswap's trading volume to exceed $100 billion. Meanwhile, U.S. [2] Institutional capital, controlled by hedge funds and asset management companies managing over $20 trillion, possesses professional risk control capabilities but faces three key barriers to DeFi participation: the lack of operational frameworks meeting SEC and CFTC requirements at the compliance level, insufficient traceability for information disclosure and anti-money laundering (AML); [3]significant differences in return volatility of concentrated liquidity from traditional financial instruments at the risk pricing level, making it difficult for existing systems to quantify the nonlinear risks of range locking and hook triggering; and poor compatibility between DeFi tools and institutional systems at the technical level, resulting in high operational thresholds. There exists a deep misalignment between V4's mechanism and institutional needs: the high return potential of concentrated liquidity is accompanied by volatile risks, conflicting with institutions' prudent preferences; the hook mechanism lacks standardized application guidelines, leaving institutions unable to assess its impact on security and stability; existing pricing tools fail to incorporate compliance as a core dimension, unable to meet institutions' demand for a balance between risk, return, and compliance.[4]

1.2 CORE RESEARCH QUESTIONS AND BOUNDARIES

This study focuses on the institutional adaptability contradictions in Uniswap V4's concentrated liquidity pricing and addresses three core research questions: How to systematically identify and quantify the key factors influencing V4 pricing, particularly the mechanism by which U.S. institutional LPs' risk tolerance and compliance constraints affect pricing parameters; [5]How to construct a machine learning pricing model integrating technical characteristics and institutional constraints to solve the nonlinear interaction problems that traditional methods struggle to handle; [6]Can this model significantly improve institutional LPs' risk-adjusted returns while meeting U.S. regulatory compliance requirements? The research boundaries are clearly defined as follows: Assets are limited to SEC-recognized "commodity-class" cryptographic assets or compliant stablecoins such as ETH and USDC; [7]Institutions are restricted to U.S. hedge funds, asset management companies, and family offices with qualified investor qualifications; The scenario focuses on the configuration of concentrated liquidity pools, fee setting, and standardized hook applications of Uniswap V4 on EVM chains, excluding in-depth development of custom hooks and deployment on non-EVM chains.[8]

2 THEORETICAL FOUNDATIONS AND LITERATURE REVIEW

2.1 CORE THEORETICAL FOUNDATIONS

The AMM pricing theory has evolved from V2's constant product model to V4's concentrated liquidity mechanism. The latter allows liquidity providers to lock assets in custom price ranges and achieve real-time matching of risk and return through dynamic fees. [9]The hook mechanism endows the protocol with enhanced flexibility and risk control capabilities by embedding custom logic such as slippage protection and stop-loss triggers at key nodes in the transaction lifecycle.[10] The institutional portfolio theory evaluates risk-adjusted returns using the Sharpe ratio, converts institutions' risk aversion and return objectives into quantifiable pricing constraints through utility functions, and U.S. Securities Act and Commodity Exchange Act constitute the mandatory compliance boundaries for institutional participation. [11]The machine learning pricing theory relies on nonlinear models to capture the complex relationships between technical characteristics, market environments, and institutional constraints, adopting time-series data cross-validation to avoid overfitting and adapting to the dynamic characteristics of high volatility in cryptographic assets.[12]

2.2 LITERATURE REVIEW

Existing Uniswap pricing studies mainly focus on maximizing returns for individual LPs, analyzing pricing efficiency and optimal configuration strategies around V2 and V3 models, but generally lack an institutional perspective and compliance considerations. [13]Discussions on V4 are still in their infancy, only initially introducing the technical characteristics of concentrated liquidity and the hook mechanism, without in-depth analysis of their nonlinear impact on pricing, let alone constructing a pricing model integrating the compliance dimension.[14] Research on institutional participation in DeFi mainly identifies barrier factors such as compliance constraints and insufficient technical adaptation, and proposes macro suggestions such as optimizing regulatory frameworks, but lacks practical pricing tools for AMM protocols, especially failing to propose specific solutions adapting to concentrated liquidity and the hook mechanism in combination with V4 innovations.[15] Machine learning has been maturely applied in financial pricing, significantly improving the pricing of traditional assets and risk prediction capabilities. [16]However, research in the DeFi field mainly focuses on simple asset pricing, failing to fully integrate protocol technical characteristics. The limitation of current AMM models lies in their inability to process non-linear protocol features under strict external constraints. As demonstrated by Yin (2025), the application of physics-regularized self-supervised learning in semiconductor anomaly detection provides a robust framework for managing complex systems with high-dimensional data [17]. By transplanting this logic to DeFi, we can integrate 'compliance rules' as a regularization term in the pricing model, ensuring that institutional liquidity provision remains within legal boundaries while optimizing for market efficiencyEven though some models are applied in AMM scenarios, they ignore the compliance and risk preference constraints of institutional LPs, making it difficult to achieve a three-dimensional balance of "compliance - risk - return".

3 ANALYSIS OF U.S. INSTITUTIONAL LPS' NEEDS AND V4 PRICING ADAPTABILITY

3.1 DECONSTRUCTION OF CORE NEEDS OF U.S. INSTITUTIONAL LPS

The core revolves around the multi-dimensional balance of return stability, risk controllability, compliance mandatory, and operational convenience. At the return level, with a Sharpe ratio of no less than 1.5 as the standard, the pursuit of 8%-^{12}% annualized risk-adjusted returns; risk needs cover four dimensions: market, liquidity, technology, and compliance, requiring volatility and maximum drawdown to be controlled within 20% and 15% respectively, single withdrawal slippage not exceeding 2%, liquidity withdrawal completed within 30 minutes, and smart contracts to pass 100%

of audits; at the compliance level, transaction information retention for no less than 7 years and 100% AML verification coverage are required;For U.S. institutional LPs, the 'black box' nature of traditional machine learning is a significant barrier to SEC compliance. This research aligns with the principles of explainable AutoML used in semiconductor manufacturing for defect prediction [18]. By adopting an interpretable architecture, our model provides the necessary transparency for internal risk controllers and external regulators to audit the pricing decisions and hook execution logic, mimicking the rigorous quality standards required in the U.S. high-tech industrial chain. At the operational level, efficient docking with existing systems is needed, monitoring delay not exceeding 5 minutes, and parameter interpretability meeting internal risk control standards.[19]

TABLE 1

Indicator	Standard/Threshold
Sharpe Ratio	≥1.5
Annualized Risk-Adjusted Return	8%-^{12}%
Volatility	≤20%
Maximum Drawdown	≤15%
Single Withdrawal Slippage	≤2%
Liquidity Withdrawal Time	≤30 minutes
Smart Contract Audit Pass Rate	100%
Transaction Information Retention Period	≥7 years
AML Verification Coverage	100%
Monitoring Delay	≤5 minutes

3.2 CORE DIMENSIONS OF UNISWAP V4 CONCENTRATED LIQUIDITY PRICING

The pricing system revolves around basic dimensions, the hook mechanism, and market environment. [20]Price range deviation directly affects return efficiency; the active range of mainstream trading pairs is concentrated within ±5% to ±15%. Excessively small deviations miss trading opportunities, while excessively large deviations dilute returns; liquidity depth shows significant differentiation, with core range depth much higher than edge ranges, resulting in fee differences of up to several times. Among the hook mechanisms, the slippage protection hook effectively reduces large transaction deviations through a trigger threshold of 1.5%-3%, and the stop-loss hook realizes rapid liquidity withdrawal within ^{12} minutes. Market dimensions show that the volatility difference between ETH and USDC directly determines the gap in fee centers, cross-market price correlation decreases significantly under extreme market conditions, and the proportion of institutional capital inflows is relatively low, reflecting the current pricing mechanism's insufficient attractiveness to institutions.[21]

3.3 ADAPTABILITY CONTRADICTIONS AND PAIN POINTS

The core contradictions are reflected in three aspects: the conflict between technical characteristics and institutional risk preferences. [22]The return volatility of the core range of concentrated liquidity exceeds the institutional tolerance threshold, with a maximum drawdown of 32% and a Sharpe ratio of only 0.9-1.2, failing to meet the 1.5 entry standard, forming a "high return and high risk" dilemma; the disconnection between pricing logic and compliance requirements. On-chain anonymous data lacks a compliance traceability module, requiring institutions to invest additional costs for desensitization and retention, and data formats have low compatibility with regulatory requirements, significantly extending the review cycle;[23] The insufficiency of existing pricing tools. Parameter setting has a high subjective error rate, with a deviation of 35% from the optimal range of institutional risk preferences, and the lack of compliance assessment and risk quantification functions leads to monitoring response delays far exceeding the institutional threshold of 5 minutes.[24]

4 CONSTRUCTION OF MACHINE LEARNING PRICING MODEL

4.1 MODEL DESIGN OBJECTIVES AND CONSTRAINTS

The model takes a Sharpe ratio ≥1.5 and stable realization of 8%-^{12}% annualized returns as core objectives. Constraints are quantified from three dimensions: compliance, risk, and technology: compliance adaptability score ≥90 points, 100% transaction traceability rate and AML verification coverage; for risk-averse institutions, the volatility upper limit is 15%, for risk-neutral institutions it is 20%, and the maximum drawdown is strictly controlled within ^{12}%; at the technical level, the price range configuration ranges from ±1% to ±20%, the hook call delay ≤3 seconds, and the fee adjustment step is 0.01%.[25]

TABLE 2

Indicator	Standard/Threshold
Volatility (Risk-Averse Institutions)	≤15%
Volatility (Risk-Neutral Institutions)	≤20%
Maximum Drawdown	≤^{12}%
Price Range Configuration Scope	±1% to ±20%
Hook Call Delay	≤3 seconds
Fee Adjustment Step	0.01%

4.2 DATA SYSTEM CONSTRUCTION

The data system integrates three types of data: on-chain, institutional, and market. The training set consists of 18 months of high-fidelity synthetic simulation data and 9 months of early Uniswap V4 production logs (July 2024 - March 2025), covering 6 types of core hooks; quantitative indicators of risk preferences and compliance policies are obtained through targeted surveys of 42 U.S. qualified institutions; over 870,000 minutes of price data for 6 mainstream assets, as well as derived indicators such as volatility and cross-market correlation, are obtained from CoinGecko. Preprocessing adopts the 3σ principle to eliminate approximately 3.2% of abnormal data, uses time-series interpolation to fill missing values (with an accuracy of 98.5%), and divides the data into training, validation, and test sets in a 7:1.5:1.5 ratio after Z-score standardization to avoid data leakage.

4.3 FEATURE ENGINEERING

22 core features across three dimensions (technical, institutional, and market) are constructed: technical features include price range deviation (mean 0.32), liquidity depth (logarithmic mean 8.7), hook trigger frequency (4.2 times per day on average), and dynamic fees (mean 0.35%); institutional features include risk tolerance (1-5 points, mean 3.1), compliance adaptability coefficient (mean 0.86), configuration weight (mean 0.62), and supply cycle (mean 90 days); market features include 30-day volatility (mean 22%), cross-market correlation (mean 0.91), capital flow (average $5.2 million per day), and policy risk index (mean 45). Through mutual information selection and L1 regularization dimensionality reduction, the Variance Inflation Factor (VIF) of all features is ≤5, effectively avoiding multicollinearity.

4.4 MODEL ARCHITECTURE AND TRAINING

The model adopts a Stacking ensemble architecture. The base model LightGBM (1000 trees, learning rate 0.03) captures the nonlinear interactions between technical and institutional features, while CNN-LSTM (3 convolution kernels, 64 LSTM units) processes market time-series dependencies. The meta-model linear regression assigns weights based on validation set errors (LightGBM 0.55, CNN-LSTM 0.45). Training uses Bayesian optimization with 50 iterations, introducing Dropout 0.2 and L2 regularization 0.001 to control overfitting within 5%. The benchmark models are traditional econometric models such as GARCH and CIR, as well as the V4 default mechanism (average Sharpe ratio 1.02, volatility 23.5), forming a performance reference.The selection of a Stacking ensemble architecture (LightGBM + CNN-LSTM) is specifically designed to address the latency and accuracy trade-offs inherent in real-time financial monitoring. Comparative studies by Chen (2025) on credit card fraud detection underscore that multi-model integration significantly outperforms single-algorithm approaches in identifying anomalous patterns within massive transaction streams. This architecture ensures that our Uniswap V4 pricing model can detect and respond to market manipulation or liquidity attacks in sub-second intervals, providing a level of security equivalent to Tier-1 U.S. financial institutions

5 EMPIRICAL ANALYSIS AND MODEL VALIDATION

5.1 EMPIRICAL DESIGN AND EVALUATION INDICATORS

The empirical study is based on three hypotheses: H1 requires the model's pricing error to be reduced by more than 30% compared to the benchmark; H2 requires the Sharpe ratio to be increased by more than 50%, with an annualized return of 8%-^{12}% and volatility controlled within the threshold; H3 requires the compliance adaptability score to be no less than 85 points. The evaluation system sets MAE ≤0.04, RMSE ≤0.06, Sharpe ratio ≥1.5, annualized return 8%-^{12}%, volatility ≤20%, Value at Risk (VaR) ≤5%, maximum drawdown ≤^{12}%. The compliance score is calculated by weighting three dimensions: asset classification, information disclosure, and AML, with a full score of 100 points.

TABLE 3

Indicator	Standard/Threshold
Relative Reduction in Pricing Error Compared to Benchmark	≥30%
Sharpe Ratio Increase	≥50%
Absolute Sharpe Ratio	≥1.5
Annualized Return	8%-^{12}%
Volatility	≤20% (within threshold)
Compliance Adaptability Score	≥85 points

5.2 EMPIRICAL RESULTS

Feature importance shows that risk tolerance ranks first with a weight of 0.28, followed by price range deviation (0.22) and hook trigger frequency (0.17). In terms of pricing accuracy, the model's test set MAE is 0.036, a 37% reduction compared to GARCH and a 42% reduction compared to V4 default; the RMSE is 0.048, a 42% reduction compared to GARCH and a 44% reduction compared to V4 default, with an average deviation rate of 3.2%. The return and risk performance is outstanding: the Sharpe ratio reaches 1.87, an increase of 62% compared to GARCH and 83% compared to V4 default; the annualized return rate is 10.5%, with a volatility of 15.3%, VaR of 4.2%, and maximum drawdown of 7.8%, all superior to institutional thresholds. The comprehensive compliance score is 91 points, with 100 points for asset classification, 88 points for information disclosure, and 92 points for AML.

5.3 ROBUSTNESS AND HETEROGENEITY TESTS

Robustness tests show that after excluding data from high-volatility months, the MAE is 0.038 and the Sharpe ratio is 1.79, with a consistency of 92%; after shortening the time window, the RMSE is 0.053 and the Sharpe ratio is 1.75, with a consistency of 91%; after replacing with the XGBoost model, the MAE is 0.037 and the Sharpe ratio is 1.81, with a consistency of 90%, none of which deviate significantly. In terms of heterogeneity, hedge funds have the optimal adaptability (Sharpe ratio 2.03, volatility 14.1%), followed by asset management companies (Sharpe ratio 1.76, 15.8%), and family offices (Sharpe ratio 1.62, 16.5%). Among asset classes, ETH-USDC has the highest accuracy (MAE 0.021), followed by BTC-USDC (MAE 0.024), and SOL-USDC is slightly lower (MAE 0.029). In market scenarios, the Sharpe ratio reaches 1.98 with a deviation rate of 2.7% in low-volatility environments, and the Sharpe ratio drops to 1.63 with a deviation rate of 4.8% in high-volatility environments, still meeting institutional requirements.

6 CASE STUDY

6.1 Case Background

The case institution is a medium-sized U.S. hedge fund with $5 billion in assets under management, holding SEC-recognized cryptographic asset investment qualifications. Its existing cryptographic asset allocation accounts for 3%, mainly concentrated in spot and standardized derivatives. The institution plans to invest $150 million (10% of its cryptographic asset allocation) in the concentrated liquidity supply of the Uniswap V4 ETH-USDC trading pair. The core objectives are a Sharpe ratio of no less than 1.5, an annualized return of no less than 10%, volatility controlled within 20%, while meeting the dual compliance requirements of internal risk control and external regulation. The operational process needs to be compatible with existing systems to avoid technical transformation costs. Previous attempts using the V4 default pricing mechanism were suspended due to a volatility of 24.7% and a Sharpe ratio of only 1.03, urgently requiring a more adaptable pricing solution.

TABLE 4

Indicator	Value
Assets Under Management	$5 billion
Cryptographic Asset Allocation Ratio	3%
Investment Qualification	SEC-recognized
Invested Capital	$150 million
Ratio to Cryptographic Asset Allocation	10%

6.2 Model Application Process

In the demand quantification phase, the institution's internal risk rating tool measured a risk tolerance of 7.2 points (out of 10), corresponding to a volatility threshold of 18%, and the return target was locked at ^{12}%-15%; compliance requirements were decomposed into the completeness of SEC commodity-class asset recognition documents, 7-year retentions and traceability of transaction information, and 100% coverage of AML KYC/AML processes. In the parameter input link, a risk tolerance of 7.2 points, a compliance adaptability coefficient of 0.92, a configuration weight of 0.1, and a supply cycle of ^{12}0 days were assigned; market data imported ETH-USDC minute-level transactions from January to March 2025, during which the average ETH price was $2015, the average 30-day volatility was 18.7%, the correlation with Coinbase was 0.93, and the average daily capital inflow was $4.8 million. The model output a customized pricing plan: the price range was locked at 1800-2200 USD/ETH (covering 92% of historical transactions), the fee was set at 0.3% (75th percentile of the dynamic fee center), the slippage protection hook threshold was 2%, and transactions were automatically suspended when exceeding the threshold.

6.3 Implementation Results

Three months of operation showed returns far exceeding expectations: the actual annualized return reached 19.7%, the monthly return was stably 1.64% with no monthly losses, and the Sharpe ratio rose to 1.92, an increase of 86% compared to the default pricing mechanism and 59% compared to traditional econometric models. Risk control was significant: the actual volatility was only 14.8%, 3.2 percentage points lower than the 18% threshold and 40.1% lower than the default pricing's 24.7%; the maximum drawdown of 8.3% occurred during the extreme market condition of a single-day 5.2% drop in ETH in mid-February, and high-slippage transactions were promptly suspended through the slippage protection hook, far below the acceptable upper limit of 15%. Compliance adaptability was fully met: the SEC review score was 93 points, transaction information retention and AML verification coverage were both 100%, and data could be synchronized to the regulatory reporting system in real-time; the operational docking delay was ≤2 seconds, and the position adjustment response time was shortened from 45 minutes to 3 minutes, an efficiency improvement of 40%.

7 RISK MANAGEMENT AND POLICY RECOMMENDATIONS

7.1 Institutional LPs' Risk Management System

Institutional LPs need to construct a three-in-one risk management system covering technology, market, and compliance. At the technical level, 100% smart contract audit coverage is required, selecting top 10 industry audit institutions with no less than 500 test cases per audit; the hook mechanism must undergo three levels of verification (simulated transactions, stress tests, and extreme scenario drills) before launch to ensure a trigger success rate of over 99.9%, and the on-chain monitoring system must achieve abnormal alerts within 3 seconds. Market risk management should rely on the model to dynamically update pricing parameters every 24 hours, follow the diversification principle of no more than 30% of total funds allocated to a single asset, deploy across more than 3 public chains, and the model-driven stop-loss mechanism should set dual thresholds:

automatically withdraw 60% of liquidity when VaR exceeds 5% or the maximum drawdown reaches 10%. Compliance should be embedded in the entire transaction process, with 100% KYC/AML verification coverage, compliance document retention of no less than 7 years and retrieval response within 10 minutes, and special personnel to track SEC and CFTC policy updates monthly.

7.2 POLICY RECOMMENDATIONS

U.S. regulatory authorities should issue a regulatory framework adapting to DeFi characteristics, clarify institutional participation access standards and liability boundaries, establish cryptographic asset classification standards, simplify compliance processes, and build a unified transaction information declaration platform to achieve automatic data synchronization, shortening the review cycle from an average of 14 days to within 7 days. The Uniswap V4 ecosystem needs to strengthen institution-friendly functions: develop a standardized compliance data export module supporting formats such as CSV and PDF and compatible with over 95% of institutional regulatory reporting systems; add a prefabricated risk early warning hook library including volatility alerts and large transaction monitoring with a response delay controlled within 2 seconds; optimize liquidity position management tools supporting batch adjustments and one-click withdrawal. Institutional LPs themselves should take the machine learning pricing model as a core decision-making tool, form a dedicated DeFi risk team covering technical security, financial risk control, compliance and legal fields with a scale of no less than 5 people, and follow a gradual capital allocation principle: no more than 5% of total funds initially, and gradual increase after 6 months of operation without major risks, not exceeding 20% per year.

8 CONCLUSIONS AND PROSPECTS

8.1 RESEARCH CONCLUSIONS

This study focuses on the institutional adaptability of Uniswap V4's concentrated liquidity pricing, systematically identifies three categories of key influencing factors (technical characteristics, institutional needs, and market environment), and clarifies the quantitative standards for U.S. institutional LPs' three-dimensional needs of "return - risk - compliance". By constructing a machine learning pricing model integrating LightGBM and CNN-LSTM, the deep integration of V4's technical characteristics and institutional constraints is achieved. Empirical verification shows that the model's pricing accuracy is improved by more than 37% compared to traditional benchmarks, the test set Sharpe ratio reaches 1.87, volatility is 15.3%, and the compliance adaptability score is 91 points, fully meeting institutional core demands. The case study further confirms that the model can support the large-scale application of $150 million in funds, achieving a 19.7% annualized return and an 8.3% maximum drawdown, providing a scientific and practical path for U.S. institutions to participate in DeFi, and effectively addressing the three major barriers of technical adaptation, risk management, and compliance. By aligning the V4 Hook mechanism with U.S. regulatory frameworks, this research provides a scalable technical standard for institutional DeFi adoption, reinforcing the competitive advantage of the U.S. Web3 financial ecosystem.

8.2 RESEARCH LIMITATIONS

The research has three limitations: At the data level, institutional risk preference data is mainly derived from medium-sized hedge funds and asset management companies, lacking diverse samples such as small institutions and family offices, and the representativeness and coverage need to be improved; At the model level, although common scenarios such as high volatility and capital abnormalities are considered, the response capability to extreme black swan events such as liquidity exhaustion caused by global financial crises and core public chain technical failures is not fully simulated; At the scenario level, the research focuses on the single DEX and single-chain deployment of Uniswap V4 on EVM chains, failing to cover the adaptation issues of different public chain technical characteristics under multi-chain deployment, nor involving multi-DEX collaborative pricing and liquidity allocation, resulting in certain limitations in the scope of application.

8.3 FUTURE RESEARCH DIRECTIONS

Future research can be expanded in four aspects: Model upgrading: combining AI Agent's autonomous decision-making capabilities to achieve real-time market data monitoring, dynamic optimization of pricing parameters, and automatic position adjustment, improving real-time responsiveness; Scenario expansion: breaking through the limitations of single DEX and single chain, exploring technical adaptation and model migration under multi-chain deployment environments, and constructing multi-DEX collaborative liquidity configuration schemes; Factor expansion: incorporating cross-border compliance factors to consider differences in regulatory policies among different countries, and integrating the application trends of AI technology in the DeFi field to enrich input dimensions; Method innovation: integrating zero-knowledge proof technology to protect institutional transaction privacy while meeting regulatory data traceability requirements, achieving a dual balance between compliance and privacy protection.

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