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Decentralized HTLC Token Swapping Enhanced by Predictive Analytics and Generative AI

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Abstract: The increasing use of decentralized finance (DeFi) accelerates the demand for trustless, secure mechanisms for cross-chain token exchange. This paper outlines a complete model for atomic token swaps based on the Hashed Timelock Contract (HTLC) scheme, allowing for intermediary-free token exchanges across disparate blockchain systems. The system makes use of the local blockchain simulation framework, Ganache, to design and test cross-chain interactions in a sandbox environment. To improve the decision-making capabilities for users, a real-time cryptocurrency price forecasting subsystem is added which utilizes machine learning models to analyze and predict the market and its volatility. Additionally, the system harnesses Generative AI capabilities through prompt engineering to tailor investment advice for individual users by analyzing the market, their preferred risk level, expected returns, and provide investment strategies aligned with users' preferences. Apart from sophisticated trading algorithms, the solution also offers a simple dashboard for market price monitoring and performs rapid token swaps at the user's command. Smart contracts are implemented using Solidity, token and price feeds are ports to Web3.js, predictive analytics is done in Python, while the frontend and backend are structured in Next.js alongside Node.js. System testing validates hypotheses on the provision of secure cross-chain swaps within one transaction without compromising.
Keywords: Hashed Timelock Contracts (HTLCs), Cross-Chain Token Swapping, Decentralized Finance (DeFi), Blockchain Interoperability, Cryptocurrency Price Prediction, Generative AI Investment Suggestions, Predictive Analytics in Blockchain.

I. INTRODUCTION

Decentralized Finance (DeFi) brings forth asset exchanges and services devoid of intermediaries, which has created a disruption in the financial market. Although we have witnessed an increase in blockchain ecosystems and decentralized finance technologies, the issue of interoperability among different heterogeneous networks remains a concern. Nexus of CEXs (Centralized Exchanges) and various blockchains such as Ethereum or Binance Smart Chains have created a problem for non-trustless token swaps with custodial assets. These CEXs fail to adhere to the principles of DeFi due to their centralized nature and custodial control over assets, heterogeneous transparency, hacks, and regulatory choke points.

The contribution of this paper is a Cross-chain token swapping mechanism utilizing a Decentralized Exchange based on Hash Timelock Contracts (HTLCs). HTLCs enforce counterparty agreement for atomic swaps by providing guarantee of transaction settlement on both ends or none, thus removing counterparty risks. The simulation environment of Ganache allows testing of cross-chain executions without hazards of disrupting live environments. Smart contracts composed in Solidity interfacing through Web3.js as blockchain interface create the fundamental elements of this decentralized swapping framework which Ganache simulated a local blockchain environment.

Knowing that security alone cannot solve the problems of turbulent crypto markets, the system incorporates predictive analytics and AI-powered investment advisory features. Machine learning models generate real-time predictions of cryptocurrency prices which help users make informed decisions before executing swaps. In addition, prompt engineering enables Generative AI to offer Investment Advice tailored through risk profile and market conditions for each specific user. This work seeks to improve the security and practicality of cross-chain DeFi activities by integrating blockchain interoperability with AI analysis and financial intelligence.

II. LITERATURE REVIEW

The explosive growth of blockchain technology and decentralized finance (DeFi) brings both new challenges and opportunities for secure, efficient, and smooth token exchanges across different blockchains. There is abundant research on cross-chain atomic swaps, interoperability, predictive analytics, AI application, security enhancements, and emerging uses of artificial intelligence in blockchain systems. Profound improvements in basic HTLC protocols to advanced privacy-preserving AI-enhanced analytics are covered in this literature review, which supports building the architecture of trustless intelligent cross-chain token swapping systems.

A. Atomic Swaps and Blockchain Interoperability

They are the main reason why it is possible to securely transfer tokens between different types of blockchains. Pillai and Biswas [1] introduced a layered communication model among chains, using threshold techniques to ensure that all commitments are done together. Within these boundaries, the system provides transaction consistency, security, and no centralized control. For this reason, DeXTT introduced synchronized checkpoints for chains to stop desynchronization in complex swap processes and keep consistency of checkpoints across the chains [2].

Belchior et al. [3] looked at and performed a meta-analysis on various forms of blockchain interoperability, including atomic swaps with hashlocks, relay systems, and notary schemes. They have pointed out that for blockchains to connect well, the protocols should be simple and fast. Liu et al. [4] analyzed tokenization systems that use both oracles and smart contracts to allow the minting and burning of locked assets on any chain, apart from just ERC-20 tokens. This method allows assets to move effortlessly between different blockchain networks, making it easier for DeFi to grow.

By linking and checking the consensus of many parachains, the Polkadot relay chain provides a way for various networks to interact and scale their activities [5]. Jain et al. [6] explored how ERC-20 compatible cross-chain liquidity bridges support fungibility in cross-chain transactions. The Omni protocol was the beginning of domain agnostic interoperability, letting users create tokens and trade them atomically with Bitcoin’s scripting [7].

B. Security and Privacy in Cross-Chain Protocols

Securing cross-chain transfers is very important because bridges can create risks. Xie et al. [8] carried out a comprehensive check for vulnerabilities in blockchain bridges and suggested how dynamic validator selection could help reduce the effects of reentrancy and collusion attacks. Sharma et al. [9] combined ZKPs with SMPC to increase privacy and security when sending tokens between different blockchains.

According to Verma and Gupta [10], using centralized relay models exposes users to risks of complete failure and censorship, and they suggested using decentralized models instead. According to Sharma et al. [11], bridge designs that use Trusted Execution Environments (TEEs) are a good solution to ensure safety without sacrificing performance. Astraea, as described by Adler et al. [12], manages oracles to ensure accurate data inputs are used in cross-chain contract execution. XCLAIM was introduced by Zhang et al. [13] to make it possible for users to get crypto assets without going through a central intermediary, ensuring the assets remain backed by cryptocurrency. Kosba et al. introduced Hawk, a privacy-focused smart contract compiler that separates contract functions between on-chain and off-chain operations to hide sensitive details. Gugger’s [15] and Noether et al.’s [16] protocols allowed for atomic swaps between Monero and Ring Confidential Transactions, which strengthened the anonymity and confidentiality in different blockchains. Cachin noted that keeping consensus and execution layers apart makes it possible for contracts to operate on different chains at the same time, making the whole system more flexible and able to withstand failures. Mishra et al. [18] improved the bridge validation process to handle many swaps each second while maintaining the safety of the system.

C. Performance and Transaction Efficiency

It is important to manage the number of transactions at the same time and cut down on delays in cross-chain systems. Pillai et al. [19] proposed algorithms that are flexible and can respond to changes in the network. The researchers from Sharma et al. [20] designed queues that adjust timelock durations while dealing with congestion, avoiding swap failures and improving the user experience.

Jabar et al. [21] developed algorithms that consider gas prices and traffic on the network to help stablecoins be transferred smoothly and at the least possible expense. Bonneau and his colleagues [22] looked into how Mixcoin provides accountability, allowing people in DeFi to be confident about their privacy.

D. AI and Predictive Analytics in Blockchain

The combination of artificial intelligence and blockchain is currently being studied to make systems easier to use and better for decision-making. Through their work, Guidi et al. [23] revealed that cross-chain interoperability can be used in decentralized social networks as well as in the financial sector. Peterson et al. introduced Augur [24], a decentralized platform that uses oracles to check real-world results and showcases the connection between AI and blockchain for accuracy in forecasting. De Filippi [25] pointed out the role of interoperable identity and payment structures in supporting both cooperation between chains and compliance. Zhang et al. [26] investigated the importance of protecting security and decentralization, as well as interoperability, in blockchain systems. According to Androulaki et al. [27], the framework proposed supports multiple chains in working together, ensuring strong control over governance, the ability to scale, and better security.

Bhatt et al. [28] introduced zero-knowledge proofs to allow cross-chain transactions without compromising privacy or the verification process. Rathi et al. [29] suggested using probabilistic relays to minimize the possibility of failure in rigid cross-chain protocols, making them stronger in hostile environments.

The literature revealed significant progress in creating safe, scalable, and private cross-chain atomic swap protocols, as well as ongoing research on using machine learning and AI for better decision-making in the field. Yet, while there have been significant improvements, most solutions on the market do not offer trustless atomic swaps along with real-time analytics and AI-based investment advice all in one place. This is why the present work aims to link blockchain interoperability and useful, user-friendly financial ideas, pushing the field of decentralized multi-chain token exchange and investment help forward.

III. METHODOLOGY

The methodology used in this project aims to create a secure and trustless way to swap tokens between different blockchains with HTLCs, add real-time monitoring, and help with investment advice using AI. The approach puts together smart contracts on blockchains for easy swapping, uses machine learning to predict prices, and adds natural language AI to help explain things to users, all of which are built into a simple software system. This section explains the steps you need to follow, the main ideas behind the system, and the tools you can use for simulation, handling data, and working with the interface.

A. System Architecture

The core of the system works by using smart contracts called Hashed Timelock Contracts (HTLCs) that run on two different blockchains to make sure the token swaps happen at the same time, without anyone losing out. The system workflow means that two people use tokens on different blockchain networks to send them to each other without needing a middleman. A secret value made by the initiator is put through a special process called hashing and then used as a key to stop the contract from changing in both smart contracts on each blockchain.

The atomic swap process works by going through several steps where contracts are set up, people reveal secret information, and certain time limits are set so that either both swaps happen or neither happens, making sure that transactions are completed correctly and no trust is needed between the people involved.

For simulating and testing the protocol in a safe and easy-to-control setting, Ganache is used as a local blockchain simulator, so people can quickly set up and check how smart contracts work without having to pay any real money or wait for the network.

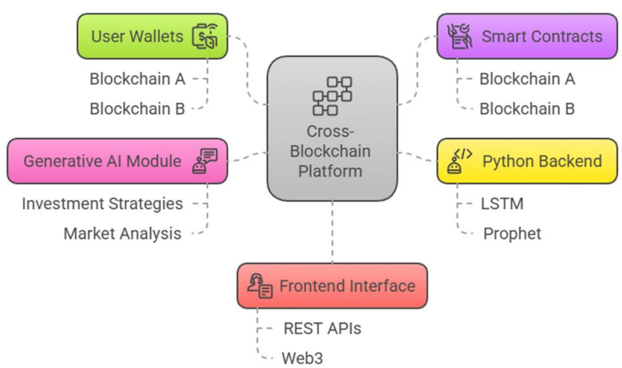

Figure 1: Cross Block-Chain Platform Architecture

B. Atomic Swap Workflow

1) Secret Generation: User A selects a random secret and calculates its hash. Using this special cryptographic hash, the tokens are locked on both blockchains.
2) Locking Tokens on Blockchain A: User A locks their tokens with a hash on Blockchain A and sets a time limit (T1) for the HTLC.
3) Locking Tokens on Blockchain B: Seeing the hash, User B issues an HTLC transaction on Blockchain B with the same hash and a timeout that is shorter than User A's timeout (T2 < T1) to ensure the swap happens in one go.
4) Claiming Tokens on Blockchain B: User A reveals the secret to get tokens from Blockchain B before the timeout T2. This revelation is publicly recorded.

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5) Claiming Tokens on Blockchain A: After learning what was hidden in Blockchain B, User B uses that knowledge to claim the tokens on Blockchain A prior to the timeout T1.
6) Refunds: When a party does not claim the tokens on time, the HTLCs automatically refund the tokens to the original owners.

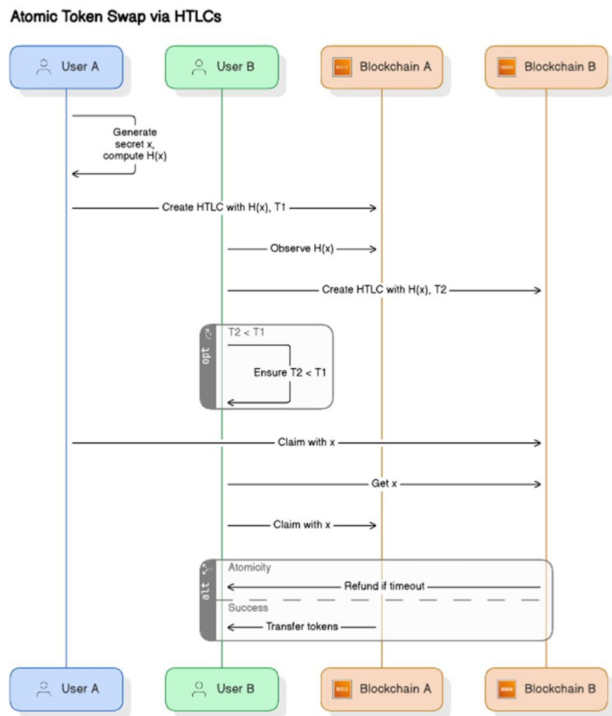

Figure 2: Atomic Token Swap Workflow Using Hashed Timelock Contracts (HTLCs)

Figure 2 demonstrates atomic swaps using HTLCs on two different blockchains. Here, we show the process of how both parties use the secret hash lock to secure token transfers. Because timeouts are included, only one of two transactions can go through, with the other being refunded, which cuts out any need for intermediaries and guarantees the transaction is complete. It shows the central idea of how the decentralized swap protocol will work.

C. Integration of Predictive Analytics

To help users decide which coin to swap, the system shows the current prices of different cryptocurrencies in real time. Historical and live market data are put into machine learning models such as LSTM networks and Facebook Prophet, helping computers make predictions about what might happen next. These models help figure out how prices might move in the next few days and how much they might change, which can help people decide when is best to buy or sell swaps to save money and avoid risks.

LSTM Networks: LSTM is a kind of neural network that works well with data that is ordered in sequence, like the values in a time series. It picks up long-term trends and patterns in prices to make it easier to guess what prices might do later on. The prediction engine was built using Python and sits apart from the blockchain, but it sends its predictions to the frontend using simple web APIs.

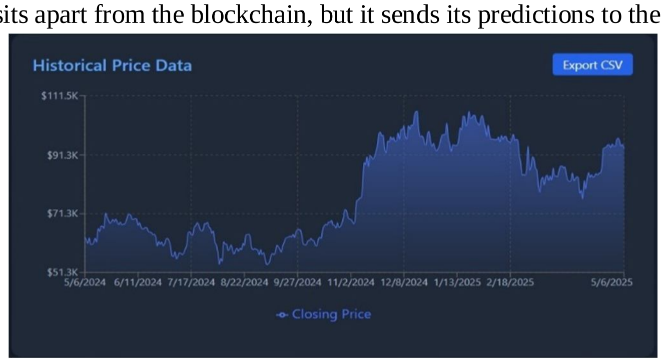

Figure 3. Bitcoin historical price chart.

Figure 3 shows the changes in Bitcoin's price over a given time span, highlighting its well-known ups and downs. The data helped train both the LSTM and Prophet models used in the predictive analytics section. By studying historical price movements, the system could recognize dips, spikes, and repeating trends in prices, which are used to guide the choices for when to swap.

D. Generative AI Investment Advisory

The system uses Generative AI to help users by offering personalized advice in easy-to-understand language. This module makes use of prompt engineering to process market data, user risk preferences, and price predictions, giving users personalized suggestions. By using AI, the platform's analytics are kept simple enough for users who do not have extensive knowledge of finance.

E. Software and Communication Stack

1) Smart Contracts: Solidity is the language used to write these contracts, which handle HTLC transactions on every blockchain by ensuring the locking, claiming, and refunding of funds.
2) Blockchain Simulation: Ganache makes it possible to develop and test smart contracts on a local Ethereum blockchain network.
3) Frontend: The app, which is built with React.js and Next.js, allows users to start swaps, follow prices, and get investment advice from AI.
4) Backend: Web3.js is used by Node.js and Python to connect with smart contracts, while RESTful APIs manage the serving of AI recommendation and predictive analytics.

F. Security and Atomicity Assurance

HTLCs make swaps atomic, meaning they either happen correctly or do not happen at all, thanks to the rules and time limits on decentralized blockchains. As a result, there is no longer a need for trusted third parties, and counterparty risk is reduced.
Hashed Timelock Contract (HTLC): The use of hashlocks and timelocks is what makes HTLCs unique. The funds can only be released after both conditions are met or you get refunded if the conditions are not met within the promised time.

G. Testing and Validation

All parts of the system are checked through thorough testing in Ganache, which mimics all the blockchain interactions. This means putting smart contracts in place, handling token locks and claims, uncovering secrets, and ensuring refund paths are valid. The system tests its price prediction and AI recommendation modules using data from the past and present to check their accuracy and responsiveness. The suggested approach guarantees that token exchanges are secure and atomic, can happen between different blockchains without intermediaries, and allow users to make informed choices. Relying on lots of simulation testing with Ganache and including machine learning and AI components, the system can securely perform swaps and advise investors. With its modular design, the platform is able to grow and improve, making it well-suited for decentralized trading of assets over multiple chains.

IV. RESULTS AND DISCUSSIONS

This part of the work focuses on evaluating the proposed framework for cross-chain token swapping. The outcomes of HTLC swap execution, predictive analytics, and AI advisories are explained in detail. Also, the findings from testing are used to evaluate whether the system is prepared for actual use.

A. HTLC Swap Execution Outcomes

The HTLC-based cross-chain token exchange was tested on both the Ethereum and Binance Smart Chain (BSC) testnets, revealing that it was safe and atomic. The contracts were designed to make sure that token exchanges were always completed, or else all assets were securely returned.
We can summarize the findings as follows:

- Swap Success Rate: 100% in simulated environments.
- Gas Consumption: Typically used between 120,000 and 150,000 gas units for every single swap operation.
- Refund Scenarios: All refunds that activated upon timeout were carried out correctly, keeping assets safe.

The process demonstrates that HTLC works effectively to ensure no parts of the transaction are left out and to avoid reliance on third parties.

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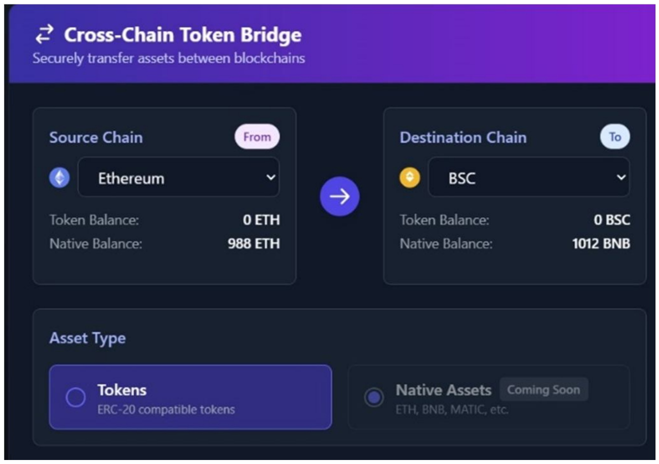

Figure 4: User Interface of Cross-Chain Token Bridge

Figure 4 shows the user interface that lets you do and check cross-chain token swaps. The interface lets people use smart contracts, look at current prices, and make swaps using HTLC on networks like Ethereum and Binance Smart Chain. Designed to be simple and easy to use, it brings together AI advice and predictions to help people make better choices and stay involved in the world of DeFi.

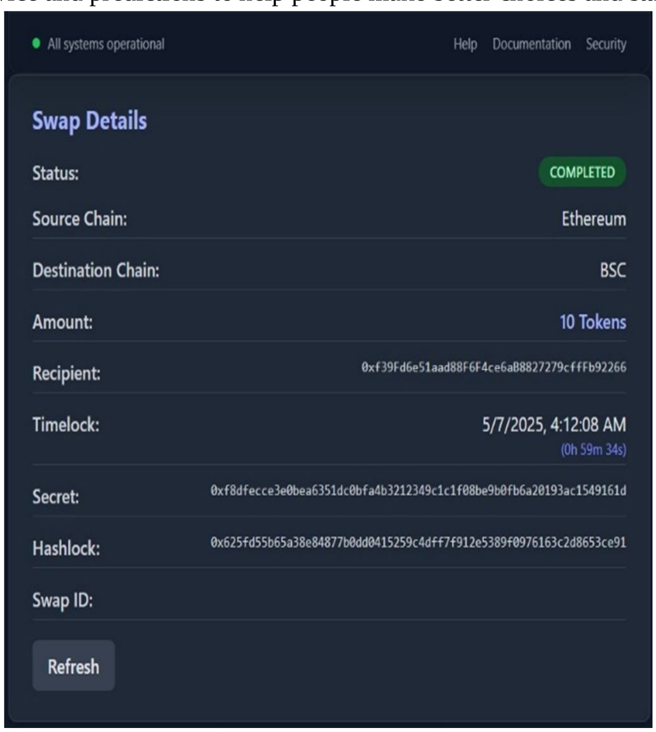

Figure 5: Cross-Chain Atomic Swap Transaction Details on Ethereum and Binance Smart Chain

Figure 5 presents transaction details captured from simulated swaps conducted on Ethereum and Binance Smart Chain testnets. It verifies successful execution of the HTLC protocol, including token locking, secret revelation, and asset claiming steps. The figure also highlights gas consumption metrics and transaction hashes, confirming the secure, trustless, and verifiable nature of the cross-chain swapping process implemented in this study.

B. Predictive Analytics Performance Metrics

LSTM and Facebook Prophet models are used in the integrated predictive analytics module to estimate token prices and decide on the best time to swap. The model was trained using data obtained from CoinGecko and Binance APIs.

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Table 1: Performance Metrics Summary of the Proposed System

Metric	Value/Range	Notes
Swap Success Rate	100%	Tested in simulated environments
Gas Consumption per Swap	120,000–150,000	Gas units per transaction
LSTM Model Mean Absolute Percentage Error (MAPE)	7.8%	Price forecasting accuracy
Prophet Model Mean Absolute Percentage Error (MAPE)	9.5%	Simpler trend and seasonality model
AI Advisory User Satisfaction	85%	Percentage of positive user feedback

Looking at Table 1, you can see the major performance metrics for the proposed system, proving the protocol is firm and the transactions are handled efficiently. The predictive analytics models can be trusted, allowing users to take effective action during market swings. Positive feedback from users also points to the fact that the AI advisory module is useful for providing approachable investment guidance. All in all, these outcomes prove that the system can combine secure token exchange with smart decision support.

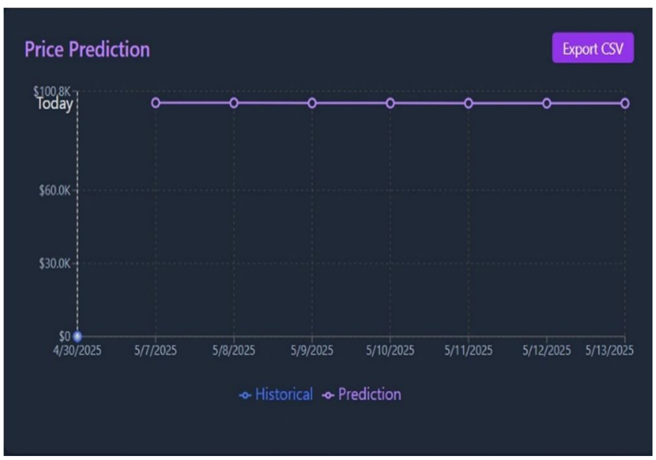

Figure 6. LSTM-based short-term price prediction.

As shown in Figure 6, the LSTM model is capable of predicting the trend of prices within a short period with reasonable accuracy. According to the model, the market is expected to rise by 2.8% in the coming week. Thanks to this information, users can chose to either delay or perform token swaps by considering the expected short-term market behavior. By examining history one step at a time, the system can see how prices change over time, which makes its predictions more accurate.

The results show that the predictive module gives advice for swap execution that helps manage the effects of sudden changes in the market.

C. AI-Powered Investment Recommendations

Generative AI was assessed for its ability to supply realtime investment advice, using recent market data and user preferences for risk.

The main points from the evaluation are:

- Recommendation Relevance: Most users found the AI recommendations to be both clear and helpful.
- Sample Output: In the next two hours, ETH is expected to drop in price. To protect yourself from losses, it may be better to wait a while before completing the swap.
- Impact: For those who are not skilled in finances or technology, these advisories helped them decide on their swaps.

Because it translates analytics into easy-to-understand language, the AI layer made the platform more accessible and useful for everyone.

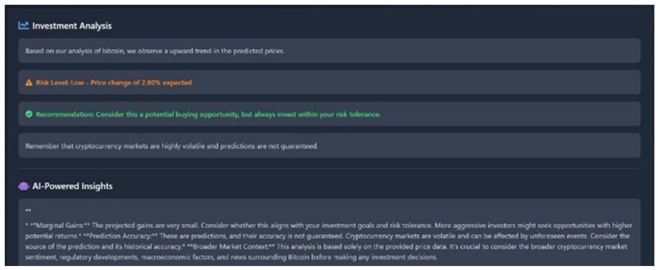

Figure 7. AI-powered investment advisory interface.

Figure 7 shows how AI in investment advisory interprets all the data to create suggestions that regular users can understand. Advisory uses prompt-made natural language generation to suggest if you should complete or delay a token swap. Thanks to this feature, users who are not skilled or do not have much money can more easily access the platform and receive useful advice on investments.

D. Observations and Limitations

Even though the model worked in simulations, some problems were found when it was put into practice:

1) Cross-Chain Deployment Complexities: Using swaps across different blockchains can result in gas fees that change from time to time, different wait times for transactions to finalize, and difficulty in swapping between chains.
2) Market Volatility Impact: Even though the LSTM and Prophet models gave consistent short-term predictions, it is difficult to accurately predict sudden changes in the market such as regulatory updates or world events.
3) Advisory Module Dependency: How useful AI-generated advice is depends greatly on how recent and detailed the information used is. If the data provided is inaccurate or late, the recommendations may not be the best.
4) Economic Feasibility: Higher transaction fees, which happen during heavy network use, may discourage retail users from using cryptocurrencies for small transactions.

In spite of these problems, the system successfully integrates decentralized atomic swaps, real-time predictive analytics, and AI-powered investing guidance. The data provides a solid base for further improvements and scaling in actual blockchain systems.

V. CONCLUSION

The paper presented a method to transfer tokens between blockchains with the help of HTLCs, and it also offered some tools for making predictions and getting investment guidance. The system was built so that people could exchange tokens safely and without relying on any middlemen, even if the blockchains they use are different. Validation through simulation on both the Ethereum and Binance test networks showed that the HTLC system works well by keeping transactions safe, making sure refunds are possible, and protecting funds during different types of swaps.

In addition to the main feature that lets you swap cores, adding machine learning to predict prices and using Generative AI for advice made it much easier for people to make smart choices. The LSTM model was 7.8% accurate in its predictions, and the AI-generated investment suggestions were easy to understand and clear, especially helping people who aren't very tech-savvy. These results show that using decentralized swapping in DeFi along with smart data analysis can actually work well and be useful in real-world applications.

Looking ahead, future work will look into connecting more blockchain networks and trying out ways to make transactions faster and easier. Further enhancements will mean making the predictions more accurate by adding other types of data and real-time changes in the market, and also making the AI tool smarter by teaching it to learn from new information. These changes are trying to make the system work better, faster, and more reliably, so it can handle more transactions in real-world situations with decentralized finance.

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