NLT - Natural Language Trader: An agentic system which allows users to easily buy crypto currency with natural language

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***Abstract*—Despite the rising global interest in cryptocurrency, trading platforms remain inaccessible to many non-technical users due to complex interfaces, unfamiliar terminology, and steep learning curves. This paper introduces Natural Language Trader (NLT)—a web-based, agentic trading system designed to simplify cryptocurrency interactions through natural language. By integrating a large language model (LLM) as a central conversational agent, NLT enables users to buy, sell, and transfer Ethereum on the Sepolia testnet using intuitive commands, eliminating the need for manual navigation or technical expertise. The system combines Gemini-powered language understanding with a rule-based command execution engine and real-time price integration, offering both automated and manual control through a minimalist UI. Evaluation results from live user testing and functional reliability assessments show that NLT successfully reduces onboarding complexity and maintains transaction safety under most conditions. The platform demonstrates the practical potential of LLMs in democratizing access to financial technologies and lays a foundation for future AI-driven crypto interfaces, including automated trading agents and broader multi-asset support.**

The prototype web page can be viewed here https://ai-trading-agent-6kpf.onrender.com/auth/

***Index Terms*—cryptocurrency, natural language processing, agentic systems, trading platforms, accessibility**

I. Introduction

A. Background and Problem Statement

The cryptocurrency market has experienced unprecedented growth, with Bitcoin recently reaching an all-time high of \$110,000 as of May 21st, 2025 [1], marking a significant milestone in digital asset adoption. This surge reflects growing institutional acceptance, declining confidence in traditional fiat currencies, and increasing mainstream awareness of cryptocurrency potential. However, despite this remarkable growth, significant barriers remain between market interest and actual participation.

Research indicates that 50% of New Zealanders express interest in cryptocurrency investing, yet many potential investors find the process confusing and technically challenging [2]. Current cryptocurrency trading platforms present substantial usability hurdles for mainstream adoption. Even established platforms like Binance require users to navigate complex interfaces [6], understand technical terminology such as "gas fees" and "slippage," and interpret market data independently. For everyday users without technical backgrounds, the process of setting up wallets, executing trades, and managing security can be overwhelming. This complexity creates a paradox where growing market interest and record-breaking prices coincide with persistent accessibility barriers.

B. Research Direction and Significance

This research attempts to solve cryptocurrency accessibility by investigating how artificial intelligence can reduce technical barriers to entry during this period of unprecedented market growth. The central research question examines: How can an LLM-driven agentive interface for crypto trading lower the technological barriers to cryptocurrency trading and facilitate broader adoption among non-technical users?

The significance of this work lies in its potential to democratize cryptocurrency access precisely when market conditions are most favorable for new participant entry. By reducing complexity through natural language interaction, such systems could enable broader participation in digital asset markets while maintaining the security and functionality that experienced users require.

C. Hypothesis

I hypothesize that a conversational interface powered by a large language model (LLM) will reduce user onboarding time compared to traditional form-based platforms and enable more users to complete trades without technical friction. I expect that users will be able to perform initial trading tasks with minimal prior knowledge of cryptocurrency terminology while maintaining high confidence in their decisions.

D. Main Contribution

To address these challenges, I present NLT (Natural Language Trader) - a web-based AI agent system that interprets user intentions expressed in natural language and executes simulated cryptocurrency transactions on the Ethereum Sepolia testnet. The system leverages advanced language models to bridge the gap between user intent and technical execution.

This paper demonstrates a working prototype that integrates large language models into a web-based trading environment, enabling users to interact naturally with live market data and execute transactions without technical friction. While operating in a simulation environment, the system serves as a proof-of-concept for future production trading platforms and provides a foundation for understanding how AI agents can facilitate cryptocurrency adoption among mainstream users during this era of historic market growth.

II. Literature Review

A. Cryptocurrencies and Their Challenges

Distrust in fiat currencies often stems from their susceptibility to inflation and devaluation due to excessive monetary expansion. In economically unstable regions with high inflation, cryptocurrencies—particularly those with fixed supply mechanisms—offer a compelling alternative for preserving wealth. For example, Bitcoin has gained popularity as a hedge against inflation, with its price reaching an all-time high of USD 110,000 as of May 21st, driven in part by the sustained weakening of the US dollar [1]. This trend reflects growing interest from foreign investors seeking protection from currency devaluation [3].

Despite this surge in interest, technical barriers continue to hinder mainstream adoption. A survey by the Australian crypto exchange Swyftx found that 43% of 2,229 respondents had never used cryptocurrency, citing uncertainty around how it works [4]. In the New Zealand context, EasyCryptoNZ reports that nearly 50% of Kiwis are either current crypto investors or are considering investing, yet many find the process of purchasing cryptocurrencies confusing and inaccessible [2]. This highlights a critical gap: the need to bridge the technical complexity of crypto trading with user-friendly, intuitive interfaces.

B. Case Study: Binance

Binance, launched in 2017, has since become the world's largest cryptocurrency exchange by trading volume [5]. While the platform enjoys generally positive user reviews, some five-star reviewers have still expressed concerns over the complexity of the user interface [6]. One user noted that Binance's feature-rich environment introduces a steep learning curve [6]. This case reinforces the earlier claim: complexity remains one of the most significant barriers to wider adoption of crypto platforms.

C. AI in Trading

The rise of Large Language Models (LLMs) marks a significant shift in how AI can support user interaction across various domains—including financial trading. LLMs are already widely used in tasks such as sentiment analysis, and their capabilities can be extended to decision-making frameworks when integrated with Deep Reinforcement Learning (DRL) [7]. Compared to traditional Natural Language Processing (NLP), LLMs offer more coherent and context-aware interactions, substantially improving the user experience [8].

However, while LLMs excel at text-based understanding and guidance, they remain fundamentally limited to language generation tasks and cannot autonomously perform system-level operations. This limitation is addressed by agentic AI systems, which integrate goal-directed reasoning, memory, and tool use. Such systems represent a critical evolution in goal-driven automation [9].

A representative example is Anthropic's Model Context Protocol (MCP), which enables models like Claude Sonnet to interface with external APIs [10]. By integrating similar architectures into cryptocurrency trading platforms, users could engage with a conversational agent that not only understands their intent but also autonomously executes transactions—effectively transforming the system from a passive assistant into an active agent capable of carrying out user-specified actions without requiring users to navigate or learn complex interfaces.

To ensure that such agents behave reliably and do not overstep user intent, the concept of mixed-initiative interaction becomes essential. Horvitz [11] outlines principles for designing systems that flexibly balance control between the user and the AI, depending on factors such as confidence level, expected utility, and context.

In agentic crypto trading systems, this principle can be applied by keeping execution under user control, with the LLM defaulting to explicit user confirmation before performing critical actions. This approach, while not probabilistically driven in this implementation, ensures a baseline level of safety and preserves user agency—key factors in fostering trust and enabling successful onboarding in high-risk environments such as cryptocurrency trading.

III. Methodologies

A. System Design

1) System Overview: Natural Language Trader (NLT) is an agentic cryptocurrency trading platform that enables users to analyse and perform trades through natural language interaction. The core benefit of NLT lies in its ability to abstract away complex user interfaces, allowing users to simply express their intent to a Large Language Model (LLM), which then interprets and executes the appropriate trading actions. This design aims to reduce the technical complexity associated with traditional trading platforms, as highlighted in [6].

The system is developed using Python's Flask framework, with an SQLite database for lightweight and rapid prototyping. For natural language understanding and interaction, NLT integrates Google's Gemini model as the central LLM agent. Real-time Ethereum (ETH) price updates are retrieved via the CoinGecko API to ensure live market context is maintained throughout the user experience.

In this prototype, ETH is the sole tradable cryptocurrency, a constraint adopted due to project time limitations. To simulate a realistic trading environment without incurring financial cost, transactions are executed on the Ethereum Sepolia testnet. Blockchain interactions—including buying, selling, and transferring ETH—are facilitated using the Web3.py library, enabling seamless communication between the backend server and the blockchain.

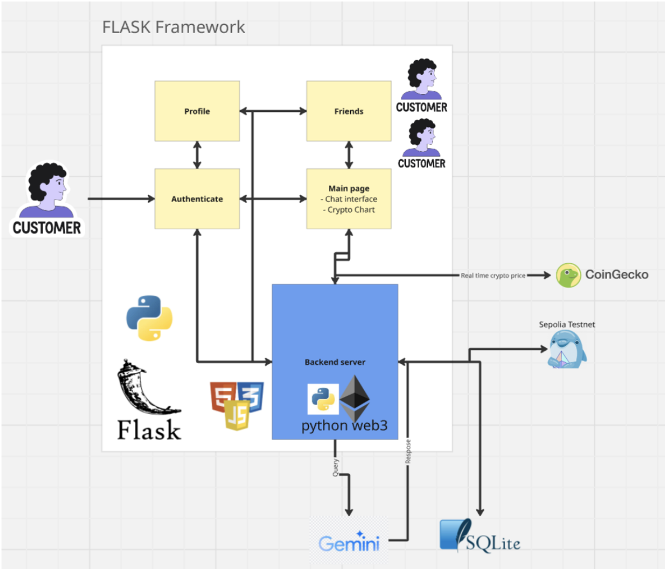

Fig. 1. System architecture of NLT - A high-level diagram showing the interaction between the user, Gemini (LLM), rule-based system, CoinGecko API, and Web3 transaction layer.

2) Design decisions: To meet the goal of reducing the technical barriers commonly encountered by new users on cryptocurrency trading platforms, I adopted a minimalist interface design that emphasizes simplicity and immediate usability. Upon login, users are routed directly to the main trading interface to give the impression that they are already inside a functional trading environment—without the need to navigate through complex onboarding menus.

At the core of this interface is a conversational chat window, prominently positioned on the left, with a clear prompt that reads "Ask me about cryptocurrencies." This prompt serves as a visual and instructional anchor, guiding users who may not know what to do next—a key aspect of effective human-computer interaction emphasized by Horvitz [11]. Adjacent to the chat interface is a real-time Ethereum price chart, reinforcing the idea that the user is operating in a live market environment.

To ensure that users retain full control, a manual trading interface is also provided on the profile page, allowing users to execute transactions without relying on the AI. This aligns with Horvitz's principle of mixed-initiative interaction, where users can override, reject, or directly invoke automated services based on their preferences or comfort level [11].

Compared to feature-rich platforms like Binance, which cater to experienced traders through a dense and customizable UI, this design deliberately avoids complexity. While Binance excels in flexibility, its interface can be intimidating to novices. The NLT interface trades breadth for accessibility, aligning with Horvitz's recommendation to minimize the cost of poor guesses and support graceful degradation—helping users advance without overwhelming them when automation is uncertain.

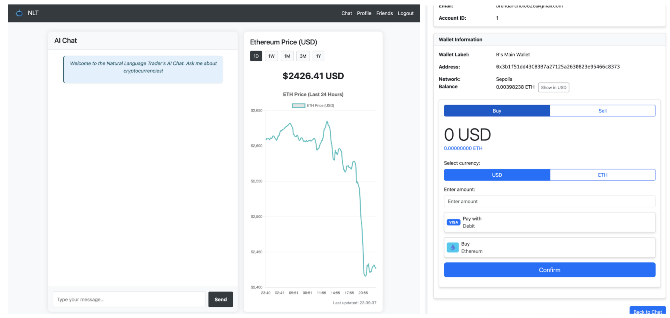

Fig. 2. NLT user interface - Main trading page and Profile page - Displays the clean dual-panel layout, highlighting the chat prompt and real-time ETH price on the main page, and manual trading features in the profile page.

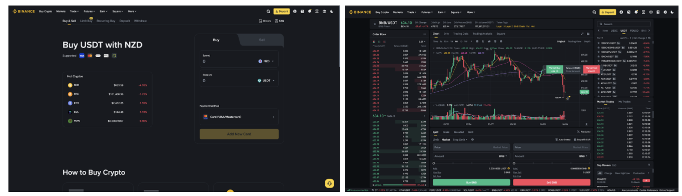

Fig. 3. Binance UI overview - Screenshots illustrating various sections of Binance's trading interface, including crypto purchase flows, market charts, and trading dashboards. These examples highlight the platform's dense layout and feature-rich environment tailored for experienced users.

B. Core components

1) Gemini: At the heart of the NLT platform is a large language model, specifically Google's Gemini-2.0-Flash [12], customized via system prompting to behave as a cryptocurrency trading assistant. Gemini serves multiple key functions: it performs market analysis through built in Google searches, summarizes relevant information, guides users through the interface, and most importantly, interprets natural language commands and translates them into structured system-level actions.

Gemini was chosen for this prototype due to its affordability and larger context window compared to other commercially available LLMs, making it well-suited for both extended interactions and low-cost deployment.

2) Rule based system: Inspired by Anthropic's Model Context Protocol (MCP) [10], the system incorporates a rule-based command execution engine. This component acts as the equivalent of the "MCP server" in the architecture, serving as a bridge between LLM output and system actions. Once Gemini generates a structured command (e.g., buy [0.5 ETH]), the rule-based system identifies the intended operation and routes it to the appropriate backend API for execution. The current implementation supports three actions: buy, sell, and transfer of testnet Ethereum tokens between user accounts.

3) Blockchain transaction system: To maintain realism in transaction handling, this prototype includes a live blockchain interaction layer rather than mock simulation. A centralized MetaMask wallet is used to store and manage all testnet Ethereum funds, allowing for actual blockchain transactions on the Ethereum Sepolia testnet.

The ETH-to-USD conversion is calculated using real-time pricing data from the CoinGecko API, ensuring that trades reflect realistic market values. While both buy and sell operations can be initiated via the LLM interface or a manual fallback UI, the transfer functionality is currently limited to the LLM interface due to time constraints and development focus on natural language interaction.

C. Workflow: Transactions

This workflow describes the end-to-end process of executing a transaction using the natural language interface in NLT.

1) User Query: The user initiates an interaction by entering a natural language instruction (e.g., "Buy $10 worth of ETH") into the chat interface.

2) LLM interpretation: Gemini processes the user input to extract the intended action (e.g., buy, sell, transfer) along with relevant parameters such as amount and recipient (if applicable).

3) Command validation: To prevent unintended actions, Gemini confirms the interpreted intent with the user. If essential details are missing or ambiguous, the model prompts the user to provide clarification.

4) Command Routing: Once the command is confirmed, it is forwarded to the rule-based execution engine (inspired by Anthropic's MCP). This system maps the structured command to the appropriate API call.

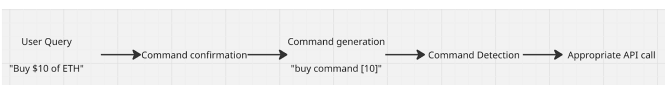

Fig. 4. Mapping Gemini Output to API Call - A visual representation of how a natural language command (e.g., "Buy $10 ETH") is interpreted and routed to the appropriate backend API.

5) Transaction: Upon receiving the API call, the backend initiates a blockchain transaction via the Web3 interface. A transaction status screen is displayed to the user to visualize progress.

6) Feedback Message: When the transaction is successfully completed on the Sepolia testnet, the system displays a natural language confirmation message, indicating the result of the operation.

D. Workflow: Market analysis

The user submits a question or request for guidance (e.g., "What's the ETH forecast?" or "How do I transfer ETH?").

1) User Query: Users will query the LLM about any crypto related questions (e.g Analysis, instructions to use the app)

2) Answer generation: Gemini performs a real-time Google search to gather relevant market information or instructional content. It then generates a structured and user-friendly response based on the retrieved data.

Users can continue the interaction with follow-up questions or initiate a transaction based on the insights provided.

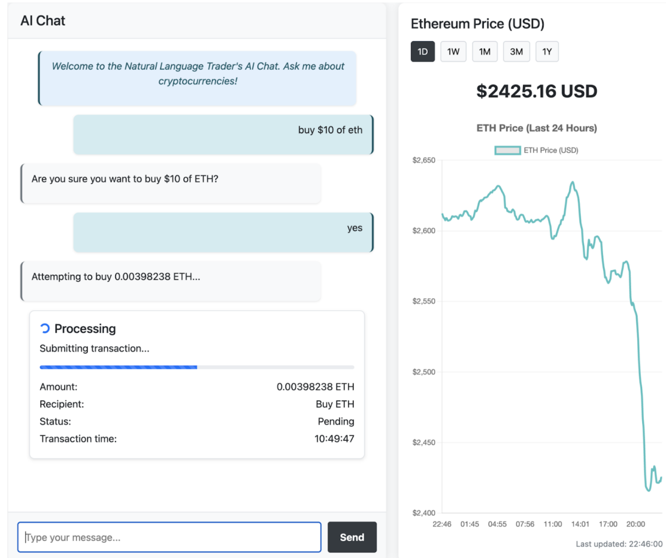

Fig. 5. Transaction Progress Screen - Displays the UI feedback during a blockchain transaction, such as loading or confirmation screens.

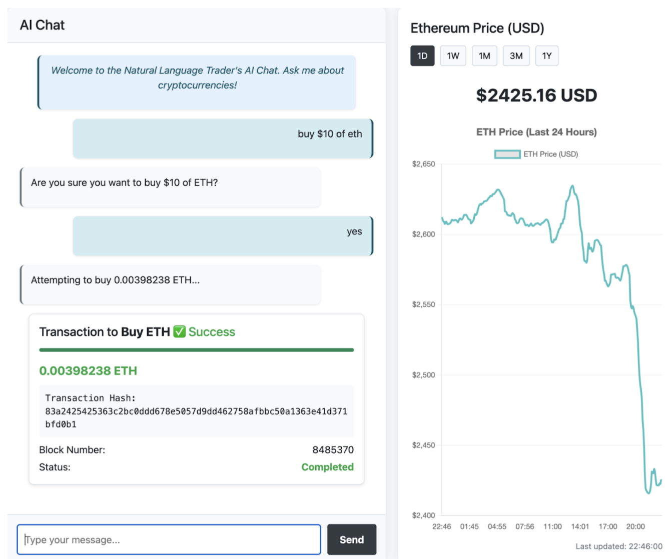

Fig. 6. Transaction Completion Message - A sample output showing natural language confirmation after the transaction is finalized.

IV. Implementation/Results

A. Usability and barrier

1) Objective: The objective of this evaluation was to determine whether an LLM-powered conversational interface could reduce the technical barriers commonly associated with cryptocurrency trading. Specifically, the goal was to assess whether users with no prior crypto experience could successfully complete basic trading tasks using the Natural Language Trader (NLT) system.

2) Participants: A small participant group of three individuals was recruited, each of whom had no prior experience or knowledge of cryptocurrency. This sample size reflects the

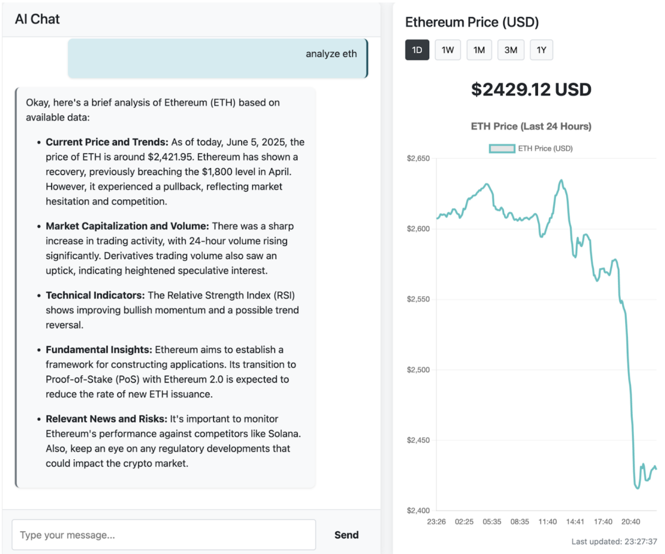

Fig. 7. Gemini-Generated Market Analysis - Example output of a prompt like "analyse eth", showing Gemini's response pulling live data.

time constraints of the project but provides valuable early insight into the system's usability for complete beginners.

3) Task Design & Metric: Participants were informed that they would complete three tasks using the agentic crypto trading platform:

- Buy ETH worth \$20
- Sell ETH worth \$20
- Ask a question about Ethereum via the chat interface

No prior training or onboarding was provided to simulate a real first-time user experience.

The evaluation metrics are summarized in Table I.

TABLE I
USABILITY TESTING METRIC

Metric	Purpose
Task Completion Rate (time limit: 5 min)	Whether the user could complete each task independently and within the time limit
Perceived difficulty	Self-reported ease of use; 1 = very easy, 5 = very difficult
Feedback	Open-ended input on what was confusing, useful, or could be improved

4) Results: The results of the usability evaluation are presented in Table II.

5) Summary: All participants successfully completed the ETH inquiry task using the chat interface in under 30 seconds, indicating strong intuitiveness for basic conversational use. However, only two out of three participants completed all assigned tasks. Participant 1 appeared confused after the first task and required help. Participant 2 completed the tasks using the manual profile page interface, while Participant 3 used the chat interface exclusively, demonstrating its full capability.

A common thread across all user feedback was the lack of clarity regarding the LLM's ability to execute trading commands. While users generally found the experience intuitive after some trial and error, they did not initially realize that buy/sell actions could be performed directly through natural language.

These findings support the hypothesis that a conversational interface can reduce technical friction—but also reveal that clear affordances or onboarding cues are necessary to fully realize the benefits of such systems.

B. Reliability of the system

1) Objective: This evaluation aimed to assess the reliability and safety of the NLT system across two key functional categories:

Ethereum market analysis, where clarity, accuracy, and consistency of LLM-generated responses were evaluated.

Transaction execution, where the system's ability to validate intent and handle ambiguous inputs was tested.

2) Task Design & Metric & Results

: **Ethereum market analysis**

To assess the consistency and clarity of the model's market insights, four commonly asked prompt types were tested. Each prompt was submitted five times, and the responses were evaluated using GPT-4o based on defined criteria. The results are shown in Table III.

Transaction Command Testing

To test the robustness of the command parsing and intent confirmation, various scenarios were evaluated across 30 interactions per category (10 for buy, 10 for sell, 10 for transfer). The system's behavior was recorded and success rates were measured. The results are summarized in Table IV.

3) Summary: The system demonstrated strong reliability in handling Ethereum market analysis tasks. Across all prompt types, Gemini consistently provided accurate, well-structured, and context-aware responses. Price trend outputs were accurate within a narrow margin, and all forecasts and news responses maintained clarity and balance.

For transaction-related tasks, initial commands were handled correctly in 90% of cases, indicating strong single-turn performance. However, ambiguity handling was a key weakness: in cases where users entered vague commands (e.g., "Buy 10"), the system interpreted the input as **10 wei** (a negligible amount). While this behavior was harmless in the current prototype, it highlights a critical risk—**in a real financial environment, the same ambiguous input could be misinterpreted as 10 ETH**, potentially leading to unintended and costly transactions. This underscores the importance of robust input validation and explicit user confirmation in future versions to ensure safety and prevent over-execution due to ambiguous commands.

These findings highlight that while the agent performs reliably for analysis and basic commands, further refinement is needed in input validation and intent disambiguation to enhance safety and robustness in real-world applications.

V. CONCLUSION

This paper presented Natural Language Trader (NLT), an agentic cryptocurrency trading platform designed to reduce

TABLE II
USABILITY TESTING RESULT

Metric	Participant 1	Participant 2	Participant 3
Task Completion Rate	1/3	3/3	3/3
Perceived difficulty	3	2	1
Feedback	"I think it would be more clear to have a guide message in the chat box that you can perform trading using the chat box. If I knew that, I think I would have been able to get a 3/3."	"I didn't know you could trade using the chat box. But I think that is a very cool idea because AI will do everything for me."	"I knew this was an agentic system so I just used the chat to see what it does, and it did it for me. But I think it's quite unclear that you can trade by typing"

TABLE III
MARKET ANALYSIS PROMPT EVALUATION

Prompt Type	Metric	Result
Ethereum price trend	Accuracy	Average error from live price $17.50 (0.69%)
Ethereum buying suggestions	Clarity and Consistency	Balanced bullish/bearish responses with consistent risk-aware phrasing
Recent Ethereum news	Clarity and Consistency	Covered all major events consistently across repetitions
One-week Ethereum price forecast	Clarity and Consistency	Clear, safe and volatility aware

TABLE IV
TRANSACTION RELIABILITY EVALUATION

Scenario	Metric	Result
Buy, sell, transfer to another user	% successful transactions	27/30 successful
Ambiguous Values (e.g., "buy 10")	% clarified	7/30 successful

technical barriers for non-technical users through natural language interaction. The system demonstrates how large language models (LLMs) can effectively bridge the gap between user intent and trading execution—addressing a significant adoption hurdle in the crypto space, where approximately 50% of New Zealanders express interest in cryptocurrency, yet many find existing platforms intimidating and inaccessible.

Evaluation results support the system's core value proposition. In reliability testing, NLT achieved high accuracy in Ethereum market analysis, with average deviation from live prices at just 0.69%, and consistently delivered balanced, risk-aware responses. The system successfully executed 90% of clearly specified trading commands, indicating strong reliability for unambiguous interactions. Most notably, participants with no prior crypto experience were able to complete core trading tasks using natural language, with two out of three achieving full task completion.

Several key strengths differentiate NLT from traditional trading platforms. First, it integrates natural language understanding with real blockchain functionality, operating on the Ethereum Sepolia testnet to deliver an authentic trading experience—without financial risk. This goes beyond simulation by enabling users to interact with actual blockchain systems.

Second, the platform adheres to Horvitz's principles of mixed-initiative interaction by balancing AI automation with user agency. Through its dual-interface design—conversational and manual—it accommodates users with varying levels of comfort and experience while maintaining transparency and control.

Third, NLT demonstrates the practical utility of LLMs in financial applications, particularly in market analysis. Gemini's ability to synthesize real-time market data and contextual information via search provides users with meaningful insights, enhancing decision-making beyond simple execution.

Finally, NLT represents a meaningful advancement toward democratizing cryptocurrency access. By abstracting complex concepts such as gas fees, wallet management, and trading commands behind intuitive natural language interaction, the system directly addresses the usability gap hindering broader adoption.

VI. LIMITATIONS AND FUTURE WORK

Despite its strengths, the current NLT prototype presents several limitations that constrain its generalizability and production readiness.

First, the limited participant sample (n=3) significantly reduces the statistical power of the usability evaluation. While early results are promising, broader conclusions cannot be drawn without a larger and more diverse user study, ideally involving 30–50 participants with varied demographic and technical backgrounds.

Second, the short development timeline constrained the depth of testing in critical areas such as security, edge cases, and robustness. For real-world deployment, the platform would require comprehensive security auditing, including penetration testing, error recovery procedures, and resistance to adversarial inputs.

Third, the system exhibited a low success rate (23%) in handling ambiguous inputs, such as interpreting "buy 10" without confirming units. This presents a major reliability concern and highlights the limitations of relying solely on static system prompts. Future iterations should include robust input validation layers, fallback dialog mechanisms, and possibly fine-tuned domain-specific LLMs to reduce hallucination and improve intent interpretation.

Additionally, NLT currently supports only Ethereum and operates exclusively on the Sepolia testnet. Expanding the system to support multiple assets, mainnet integration, and fiat onramps would be necessary to make it applicable for real-world trading scenarios.

User testing also revealed unclear affordances in the interface. While the natural language interaction proved effective once understood, most users initially failed to recognize that the chat interface could initiate trades. This underscores the need for improved onboarding flows and progressive disclosure techniques, such as contextual tooltips or guided walkthroughs.

As a next step, I propose integrating automated trading capabilities using a multi-agent system. This architecture would consist of:

A Market Analysis Agent (Gemini): retrieves and interprets real-time news and sentiment from the web,

A History Agent (LSTM-based model): analyses historical price patterns and market trends,

A Decision-Making Agent (Deep Q-Network based model): learns optimal trading strategies through reinforcement learning.

This approach, inspired by [13], would allow the platform to offer reliable automated trading options for beginners, enabling them to participate in the market with limited manual input while still benefiting from explainable and adaptive AI-driven strategies.

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