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# **Reducing Cognitive Load in Cryptocurrency Trading: An Empirical Evaluation of an Integrated Browser Overlay for Information Fragmentation**

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# Table of contents

Table of contents .....	ii
List of illustrations.....	vi
List of tables.....	ix
List of Abbreviations .....	x
Abstract .....	xi
1 Introduction.....	1
2 Literature Review and Theoretical Framework .....	5
2.1 Information Fragmentation in Cryptocurrency Trading Environments.....	5
2.1.1 Trading Strategy Differentiation in Cryptocurrency Markets .....	6
2.2 Social Media Influence on Cryptocurrency Price Formation.....	7
2.3 Cognitive Load Theory in Financial Decision-Making.....	8
2.4 Browser-Based Tools and Extensions in Trading Applications.....	10
2.5 Human-Computer Interaction in Trading Interface Design .....	11
2.6 Research Gap and Theoretical Integration .....	12
3 System Design and Implementation.....	16
3.1 Overview .....	16
3.2 Overlay User Interface and Feature Set .....	16
3.2.1 Primary Interface Components.....	17
3.2.2 Automatic Token Detection and Social Media .....	18
3.2.3 Extended Analytics View .....	19

3.2.4	Advanced Security and Network Analysis.....	20
3.2.5	Search and Discovery Features.....	21
3.2.6	Workflow Integration and Context Preservation.....	22
3.3	Four-Layer Architecture Design .....	23
3.3.1	Layer 1: Browser Extension Core .....	24
3.3.2	Layer 2: Token Detection and Highlighting .....	25
3.3.3	Layer 3: Overlay User Interface .....	26
3.3.4	Layer 4: Event and Data Flow Management.....	26
3.4	External API Integration.....	27
3.5	User Interface Design Principles .....	28
3.5.1	Cognitive Load Reduction Through Design.....	28
3.5.2	Workflow Integration Strategy.....	29
3.6	Performance Optimization and Scalability .....	29
3.6.1	Response Time Optimization .....	29
3.6.2	Scalability Considerations .....	30
3.7	Security and Privacy Implementation .....	30
3.8	Development and Testing Framework.....	31
4	Methodology .....	32
4.1	Research Design.....	32
4.2	Participants .....	32
4.3	Session Procedure and Tasks.....	33
4.3.1	Session Procedure.....	33

4.3.2	Tasks .....	35
4.4	Statistical Analysis and Analytical Framework .....	36
4.4.1	Data Collection .....	37
4.4.2	Data Preparation & Reliability .....	37
4.4.3	Statistical Methods.....	37
4.4.4	Hypotheses .....	38
5	Results.....	40
5.1	Performance Outcomes.....	40
5.1.1	Time-Based Performance.....	40
5.1.2	Behavioral Fragmentation Metrics .....	41
5.1.3	Task-Specific Accuracy.....	42
5.2	Subjective Outcomes .....	43
5.2.1	System Usability and User Experience.....	44
5.2.2	Cognitive Workload Assessment.....	45
5.3	Correlation findings .....	47
5.3.1	Within-Block Relationships .....	47
5.3.2	Within-Subject Change Relationships .....	49
5.4	Order effects .....	51
5.5	Hypotheses Summary .....	52
6	Discussion .....	54
6.1	Principal Findings .....	54
6.2	Theoretical Implications for Cognitive Load Theory .....	55

6.3	Practical Implications for Cryptocurrency Trading Interface Design .....	56
6.4	Limitations and Methodological Considerations .....	57
6.5	Future Research Directions .....	59
6.6	Conclusion .....	60
References .....		62

## List of illustrations

Figure 1: Number of tweets (solid) and rate (dashed) of PinkCoin over a time period of 45 days. A moderate Pearson correlation ( $r= 0.438$ ) between the price of PinkCoin and the number of tweets referring to the cryptocurrency is visible. ....	8
Figure 2: Main overlay interface showing token details, integrated price chart, and quick-action trading buttons. ....	17
Figure 3: Overlay integration with Twitter/X, showing contextual token information alongside social media content. ....	18
Figure 4: Extended overlay view with detailed trading statistics, security indicators, and multi-timeframe price performance. ....	20
Figure 5: Security & Network Analysis module showing risk factor validation indicators, insider network size and volume metrics, individual network breakdowns, and top holder concentration analysis with ownership percentages. ....	21
Figure 6: Search interface and token comparison features, showing multi-token lookup capabilities and search result presentation. ....	22
Figure 7: ICTO system architecture, illustrating the four-layer modular framework for browser-based integration and real-time data aggregation. ....	24
Figure 8: ICTO overlay interface demonstrating cognitive load reduction through integrated information architecture. Primary information elements (price, market capitalization, volume) are prominently displayed in the upper section, while secondary information elements (technical indicators, social metrics, security data, transaction data) are systematically organized below. ....	28
Figure 9: Experimental session structure, showing the counterbalanced protocol with sequential browser and overlay conditions, break, and metrics collection. ....	34

Figure 10: Time-based performance comparison showing total task time, Task 1 time, and Task 2 time (in minutes) across standard browser condition (A - No Ext) and ICTO condition (B - Ext).....	41
Figure 11: Error count, tab count, and platform switching frequency across standard browser condition (A – No Ext) and ICTO condition (B – Ext), visualized as boxplots. ....	42
Figure 12: Token identification accuracy in Task 1 showing coins recognized (raw count) across conditions, with individual data points overlaid. ....	43
Figure 13: System Usability Scale (SUS) results for the ICTO condition showing mean score with 95% confidence interval on 0-100 scale, with red dashed reference line at 68 indicating industry benchmark for comparison. ....	44
Figure 14: User Experience Questionnaire (UEQ) subscale scores for the ICTO condition (Block B – Ext), showing group means with 95% confidence intervals on a 1–7 scale.....	45
Figure 15: NASA-TLX subscale comparisons between standard browser condition (A – No Ext) and ICTO condition (B – Ext). Means with 95% confidence intervals are shown for all six workload dimensions (Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, Frustration).....	46
Figure 16: Correlations of within-subject change scores ( $\Delta = B - A$ ) for key variables, shown as scatterplots with regression overlays and 95% bootstrap confidence intervals. Panels illustrate relationships between $\Delta$ Effort and $\Delta$ Total time, $\Delta$ Mental and $\Delta$ Total time, $\Delta$ Effort and $\Delta$ Errors, and $\Delta$ Effort and $\Delta$ Platform Switches. ....	48
Figure 17: Heatmap of Spearman correlations for subjective and objective variables within the ICTO overlay condition (Block B). Filled dots mark correlations that are	

Holm-significant, illustrating the relationships among usability, workload, performance, and behavioral metrics when using the ICTO system. ....	49
Figure 18: Correlations between subjective and objective measures within the ICTO overlay condition (Block B), visualized as 2×2 scatterplots with regression lines and 95% confidence intervals. Each panel displays relationships (Spearman’s $\rho$ ) between: SUS vs. total time, UEQ Efficiency vs. total time, TLX Effort vs. total time, and coins recognized vs. Task 1 time.....	50
Figure 19: Complete change score correlation matrix displayed as heatmap, with Holm-significant cells marked with dots. ....	51



## List of tables

Table 1: Summary of interconnected challenges in implementing cognitive support systems in cryptocurrency trading environments .....	15
Table 2: Task Overview for both Blocks.....	36
Table 3: Hypotheses Summary .....	53

## List of Abbreviations

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API	Application Programming Interface
CI	Confidence Interval
DEX	Decentralized Exchange
FDV	Fully Diluted Valuation
GDPR	General Data Protection Regulation
HCI	Human–Computer Interaction
ICTO	Integrated Cryptocurrency Trading Overlay
MC	Market Capitalization
NASA-TLX	NASA Task Load Index
SUS	System Usability Scale
UEQ	User Experience Questionnaire
UI	User Interface
UX	User Experience
SOL	Solana (native token)
SD	Standard Deviation
$\alpha$	Significance level
$\rho$	Spearman rank correlation
$\Delta$	Change score (B – A)
p_Holm	Holm-adjusted p-value
d <sup>z</sup>	Cohen’s d for paired designs

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# Abstract

Cryptocurrency traders face substantial cognitive demands from processing multiple fragmented sources across venues and social platforms, creating cognitive overload that impairs decision-making efficiency. Existing browser-based trading tools emphasize security and performance while neglecting cognitive support capabilities, representing a significant research gap in human-computer interaction for financial technologies. This study evaluated the Integrated Cryptocurrency Trading Overlay (ICTO), a browser extension designed to reduce cognitive load through contextual information integration within social media trading workflows. A within-subjects experimental design with 15 experienced cryptocurrency traders compared standard browser workflows against ICTO-enabled conditions across two realistic trading tasks. Participants analyzed tokens and simulated trades using a standardized Twitter feed while behavioral fragmentation metrics (tab count, platform switches, errors), performance measures (completion time, accuracy), and subjective assessments (NASA-TLX, SUS, UEQ) were collected. ICTO produced substantial improvements across all measures, with task completion time decreasing 58% (Cohen's  $d^z = 1.64$ ), while behavioral fragmentation showed dramatic reductions of 87% fewer browser tabs ( $d^z = 2.53$ ), 91% fewer platform switches ( $d^z = 2.20$ ), and 85% fewer errors ( $d^z = 2.36$ ). NASA-TLX scores revealed significant cognitive load reductions across all dimensions, with effort decreasing from  $M = 6.4$  to  $M = 1.5$  ( $d^z = 7.29$ ). Correlation analysis revealed effort reduction as the primary mediator between interface design and performance gains ( $\rho = -0.70$ ,  $p_{\text{Holm}} = 0.015$ ), while system usability was excellent (SUS  $M = 86.3$ ). The findings demonstrate that ICTO successfully addresses information fragmentation challenges in cryptocurrency trading through contextual information integration, showing that browser-based overlay

technologies can serve as effective cognitive prosthetics, with effort reduction representing the most sensitive indicator of interface effectiveness in high-tempo decision-making contexts. Results have immediate implications for cryptocurrency platform development and broader applications to information-intensive professional domains.

*[Keywords: cognitive load; cryptocurrency trading; browser-integrated overlay; information fragmentation; NASA-TLX]*

# 1 Introduction

The global cryptocurrency market, valued at over \$2.3 trillion in 2024, has become one of the most rapidly evolving and complex trading environments in modern finance[1]. Unlike traditional financial markets which operate through centralized exchanges with standardized information flows, social media-driven cryptocurrency trading - particularly prevalent in meme coin and emerging token markets - requires participants to synthesize information from fragmented sources across social media platforms, on-chain analytics, technical analysis tools, and market data aggregators under extreme time pressure. This information fragmentation creates unprecedented cognitive demands for traders, who must navigate between disparate platforms while making high-stakes financial decisions in markets characterized by extreme volatility and time-sensitive opportunities [2].

Research reveals the scale of these psychological and cognitive challenges. Studies have found that cryptocurrency traders experience significantly higher levels of psychological distress, perceived stress, and sleep disruption compared to non-traders. The constant information overload from multiple sources creates what researchers term "cognitive overload," as traders struggle to filter signal from noise across unstructured information streams while maintaining awareness of rapidly changing market conditions. These challenges are compounded by the 24/7 nature of cryptocurrency markets, which creates persistent stress and affects decision-making capabilities [3].

Social media platforms have emerged as primary drivers of cryptocurrency price formation, fundamentally altering traditional information hierarchies in financial

markets. Twitter, Discord, and Telegram serve as critical sources for trading signals, sentiment analysis, and viral content that can trigger substantial price movements[4]. However, relying on social media creates additional cognitive burden. Traders must sort useful information from misinformation across multiple platforms, with research showing that information overload from diverse sources significantly hinders decision-making in trading environments [5].

Current cryptocurrency trading interfaces fail to address these cognitive demands adequately, requiring traders to maintain multiple browser tabs, navigate between platforms repeatedly, and manually synthesize information from disparate sources. This fragmented approach results in significant task-switching costs, elevated cognitive load, and suboptimal decision-making efficiency [6]. While browser extensions and overlay technologies offer potential solutions for information integration, existing tools focus primarily on data aggregation rather than cognitive load reduction and workflow optimization [7].

This work addresses these limitations by developing and empirically evaluating the Integrated Cryptocurrency Trading Overlay (ICTO), a browser extension specifically designed to reduce cognitive load and optimize task efficiency in social media-intensive cryptocurrency trading environments, with particular relevance to meme coin and emerging token trading where social signals drive price formation. The ICTO system provides real-time integration of social media content, market data, and security analysis directly within existing trading workflows, eliminating the need for constant platform switching while supporting informed decision-making under time pressure.

This study contributes to human-computer interaction and decision support research in several ways. It extends Cognitive Load Theory to high-stakes financial decision-

making and applies distributed cognition principles to cryptocurrency trading. The methodology uses validated workload assessment tools and behavioral metrics to measure interface effectiveness. Practically, it provides evidence for designing cognitive support systems in complex, multi-source information environments [8].

The main research question is: To what extent does a browser-integrated overlay reduce cognitive load and improve task efficiency in social media-driven cryptocurrency trading workflows? Supporting questions explore the overlay's impact on behavioral fragmentation (like tab and platform switching), cognitive load across different dimensions, and users' perceptions of usability and information integration.

Based on these research questions, we state the following directional hypotheses:

- H1: ICTO reduces task completion time.
- H2: ICTO reduces information-retrieval errors.
- H3: ICTO lowers NASA-TLX workload.
- H4: ICTO reduces behavioral fragmentation (tabs and platform switches).
- H5: ICTO improves perceived usability and user experience (SUS, UEQ).

Operational definitions and testable sub-hypotheses (e.g., H2a–H2c; H4a–H4f) are specified in §4.4, and outcomes are summarized in §5.5 (Table 3).

To address these research questions and hypotheses, this study employed a within-subjects experimental design with fifteen experienced cryptocurrency traders completing identical trading tasks under control and experimental conditions. The control condition required participants to use standard browser-based workflows and any available tools, while the experimental condition provided access to the ICTO system. Comprehensive data collection included objective performance metrics,

behavioral fragmentation indicators, validated cognitive workload assessments, and usability evaluations.

The remainder of this thesis is organized as follows. Chapter 2 presents a comprehensive literature review and theoretical framework, examining information fragmentation in cryptocurrency trading, social media influences on price formation, Cognitive Load Theory applications in financial decision-making, and human-computer interaction principles for trading interface design. Chapter 3 details the system architecture and implementation of the ICTO browser extension, including technical specifications, user interface design principles, and data integration approaches. Chapter 4 describes the experimental methodology, covering participant recruitment, task design, data collection procedures, and statistical analysis strategies. Chapter 5 presents empirical results, including objective performance metrics, behavioral fragmentation indicators, cognitive workload assessments, and usability evaluations. Finally, Chapter 6 discusses the theoretical and practical implications of these findings, acknowledges study limitations, and proposes directions for future research.



## 2 Literature Review and Theoretical Framework

### 2.1 Information Fragmentation in Cryptocurrency Trading Environments

Cryptocurrency trading operates within fundamentally different information ecosystems compared to traditional financial markets [7]. Unlike conventional trading environments that rely on centralized exchanges and standardized data feeds, cryptocurrency markets are characterized by extreme information fragmentation across multiple platforms, sources, and formats [6]. Crypto trading workflows span multiple heterogeneous sources. Markets are fragmented across numerous exchanges, and Twitter sentiment/activity is predictive of crypto returns, forcing traders to aggregate information across venues and platforms [9], [10], [11]. This information fragmentation creates what Yimin Du and Guolin Tang (2024) term ‘cognitive scatter’, where traders experience decreased decision-making efficiency due to the mental overhead required to navigate between disparate information sources [11].

The temporal dynamics of cryptocurrency markets exacerbate these fragmentation challenges [3]. Cryptocurrency price movements often occur within seconds of new information being released, creating extreme time pressure for traders to synthesize data and make rapid decisions [3]. This temporal constraint is particularly pronounced in meme coin trading, where viral social media content can trigger price movements of over 1000% within minutes [4].

Social media platforms have emerged as primary information sources for cryptocurrency trading decisions, fundamentally altering traditional information

hierarchies in financial markets [5]. Unlike regulated financial communications, social media information lacks standardization, quality control, or temporal organization, forcing traders to manually filter signals from noise across multiple streams. Urgenc and Tas (2024) identified Twitter as the most influential platforms for cryptocurrency price formation, with information propagation occurring through complex network effects rather than traditional authoritative sources [10].

### 2.1.1 Trading Strategy Differentiation in Cryptocurrency Markets

Cryptocurrency trading encompasses fundamentally different information processing demands depending on the underlying trading strategy and asset type. Understanding these differences is crucial for contextualizing the cognitive load challenges addressed in this study.

Social Media-Driven Trading represents a distinct approach primarily focused on newly launched tokens, meme coins, and community-driven projects where price formation occurs through viral social media content, influencer endorsements, and crowd sentiment rather than traditional financial metrics. Research indicates that meme coin prices can experience 1000%+ movements within minutes of trending social media posts, creating extreme time pressure for information synthesis across platforms like Twitter/X, Discord, and Telegram. This trading style requires continuous monitoring of multiple social media streams, rapid sentiment interpretation, and near-instantaneous execution decisions.

Technical Analysis-Driven Trading focuses on price patterns, volume analysis, and market structure using established cryptocurrencies like Bitcoin and Ethereum. These traders primarily utilize centralized platforms such as TradingView, specialized exchanges, and quantitative analysis tools, with social media playing a supplementary rather than primary role in decision-making processes.

Fundamental Analysis-Driven Trading emphasizes blockchain technology evaluation, tokenomics assessment, and long-term project viability. This approach typically involves research across whitepapers, development repositories, and financial metrics rather than real-time social media monitoring.

The cognitive demands and information fragmentation challenges vary significantly across these approaches. Social media-driven trading faces the most severe information fragmentation due to the unstructured, high-velocity, and multi-platform nature of social signals. Traders must simultaneously process Twitter feeds, Discord channels, Telegram groups, and on-chain data while maintaining awareness of rapidly changing market conditions [5] [13].

This study specifically addresses the cognitive challenges inherent in social media-driven cryptocurrency trading, recognizing that the information processing demands, time pressures, and platform fragmentation in this domain create unique interface design requirements distinct from other cryptocurrency trading approaches.

## 2.2 Social Media Influence on Cryptocurrency Price Formation

Social media now plays a direct, powerful role in shaping cryptocurrency prices - a stark contrast to the regulated information flow of traditional markets. Here, viral sentiment and community narratives often override classic analysis, driving rapid price changes [11], [13].

Research shows social media sentiment can predict short-term price swings, with Twitter sentiment correlating to price volatility and delivering predictive accuracy of 73-77% for major coins like Bitcoin (correlation coefficients between 0.30 and 0.68) [10], [14], [15].

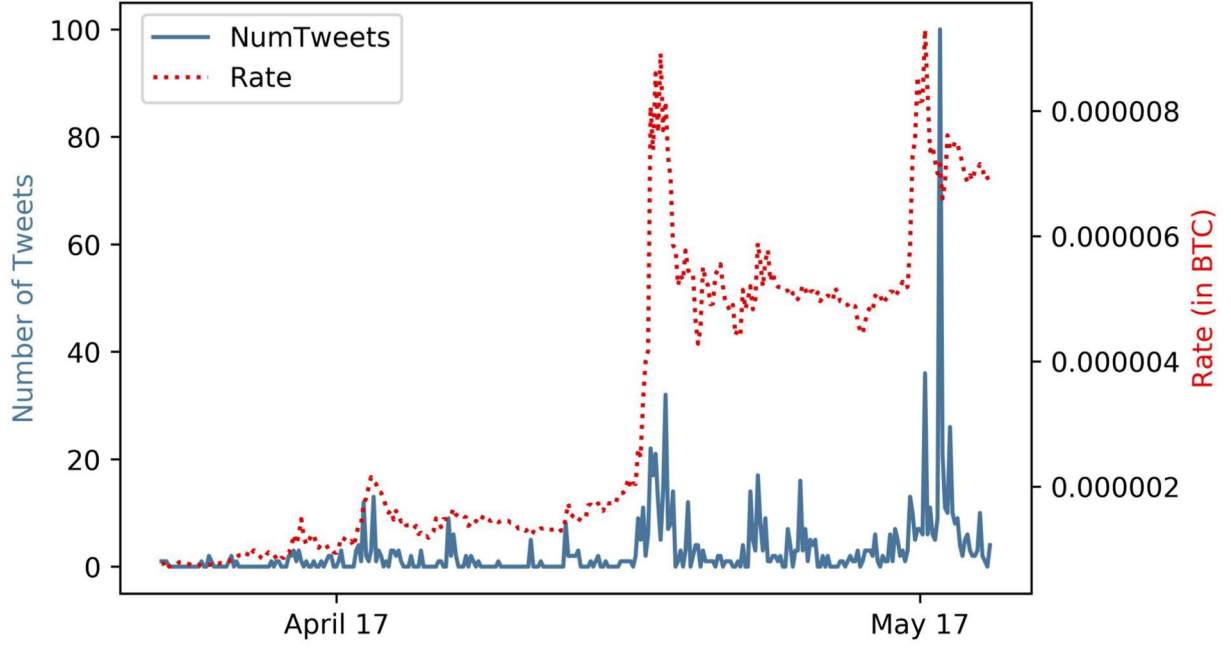


Figure 1: Number of tweets (solid) and rate (dashed) of PinkCoin over a time period of 45 days. A moderate Pearson correlation ( $r=0.438$ ) between the price of PinkCoin and the number of tweets referring to the cryptocurrency is visible.

These effects are extremely time-sensitive: market signals from social events are often valuable for just 5-30 minutes, demanding near-instant reactions - well beyond typical human processing speeds without technical help [14].

Social media shapes trading through sentiment effects, viral amplification, and algorithmic trading that reacts within milliseconds - much faster than humans. As a result, traders face the hefty challenge of monitoring platforms, interpreting sentiment, and anticipating both human and bot trades under relentless time pressure. This environment demands new approaches to synthesize and act on information rapidly.

## 2.3 Cognitive Load Theory in Financial Decision-Making

Cognitive Load Theory offers a clear lens for understanding the unique mental strain of crypto trading. It distinguishes between the effort required by complex tasks

(intrinsic load) and the added burden from poorly designed, fragmented interfaces (extraneous load) [8], [12].

Recent applications of Cognitive Load Theory to financial decision-making have revealed specific patterns relevant to cryptocurrency trading interfaces. Research examining cryptocurrency traders has documented significantly higher psychological distress and cognitive demands compared to traditional financial market participants, with studies showing that crypto traders exhibit elevated anxiety, depression, and stress levels linked to market volatility and information processing requirements [2].

The concept of cognitive offloading - strategically transferring mental processing tasks to external tools - has gained substantial empirical support in high-stakes decision-making environments. Studies demonstrate that effective cognitive offloading requires careful consideration of costs and benefits, as offloading can improve immediate task performance while potentially reducing long-term memory formation for the offloaded information.

Successful systems must provide intelligent filtering, contextual prioritization, and temporal relevance indicators to support human decision-making under extreme time pressure [15].

Working memory limitations become particularly problematic in cryptocurrency trading due to the volume and variety of information requiring simultaneous processing. Contemporary research suggests that working memory capacity is limited to approximately four distinct information chunks that can be maintained simultaneously, with performance degrading significantly when this capacity is exceeded. Their findings suggest that successful trading interfaces must minimize working memory demands through strategic information architecture rather than simply providing comprehensive data access [16].

## 2.4 Browser-Based Tools and Extensions in Trading Applications

The adoption of browser extensions for financial trading has grown substantially, with recent research examining both benefits and limitations of this technological approach. Browser extensions offer unique advantages for trading applications, including seamless integration with existing web-based workflows, cross-platform compatibility, and the ability to overlay information directly onto trading-relevant websites without requiring separate application windows.

Performance considerations for browser extensions in trading contexts have received increased attention following studies demonstrating significant impacts on system responsiveness. Jin, Li, and Zou (2024) conducted comprehensive performance analysis of 72 popular browser extensions across 11 categories, finding that extensions can negatively impact user-perceived performance metrics including energy consumption and page load time, even when extensions are used in unintended circumstances. Their research demonstrated that code complexity and privacy practices significantly influence performance impact, with some extensions causing substantial resource consumption [17].

Security and privacy concerns represent critical considerations for browser extensions handling financial information. Recent security research has documented significant vulnerabilities in cryptocurrency-related browser extensions. Wang et al. (2022) conducted an 18-month study monitoring cryptocurrency-themed extensions across seven distribution venues, collecting 3,599 unique extensions and identifying 186 malicious ones (5.17% rate). Their analysis revealed that malicious extensions caused estimated financial losses of over \$1 million, with attackers routinely posting fake positive reviews to disguise malicious intent [18].

Additional research has identified specific attack vectors, with security researchers documenting 49 malicious Chrome browser extensions targeting cryptocurrency wallets from major platforms including MetaMask, Trezor, and Ledger. These extensions employed phishing techniques to steal private keys and mnemonic phrases, with attackers using Google Ads to drive traffic to malicious extensions [19].

User adoption patterns for trading-focused browser extensions reveal important behavioral insights. The Ontario Securities Commission (2023) surveyed 2,360 Canadians including 602 cryptocurrency asset holders, finding that 52% acquired crypto assets through trading platforms, with browser-based trading interfaces representing a significant access method. The study revealed that crypto traders exhibited varied usage patterns, with 53% trading six or more times per year, indicating active engagement with browser-based trading tools [20].

## 2.5 Human-Computer Interaction in Trading Interface Design

Human-Computer Interaction (HCI) research in financial trading has evolved significantly with the emergence of cryptocurrency markets and their unique interface requirements. Traditional HCI principles developed for conventional trading platforms require substantial adaptation for the high-frequency, multi-source information environments characteristic of cryptocurrency trading.

Recent research examining information presentation in trading interfaces has revealed critical insights about cognitive load management. Studies demonstrate that increased information availability can paradoxically reduce trading performance by overwhelming users' cognitive processing capabilities. Field experiments with over 800 participants found that traders who customized their interfaces to display more information elements exhibited significantly worse decision accuracy, highlighting the

importance of strategic information architecture in reducing extraneous cognitive load [21].

Research on investment application design patterns reveals how interface fragmentation affects user behavior and cognitive processing. Analysis of popular trading platforms identified that users frequently switch between multiple information sources and applications during trading sessions, creating substantial task-switching costs and cognitive overhead. These findings demonstrate the need for integrated information presentation approaches that minimize context switching while supporting comprehensive market analysis [22].

The concept of situated cognition has particular relevance for cryptocurrency trading interface design, where information value depends heavily on temporal and contextual factors. Cognitive science research demonstrates that effective information processing occurs when relevant context is temporally and spatially integrated with decision-making tasks. In trading environments, this suggests that overlay systems providing contextual information directly within existing workflows can reduce cognitive load compared to fragmented multi-platform approaches [23].

User experience research in cryptocurrency platforms specifically addresses the cognitive challenges of information fragmentation. Studies evaluating crypto exchange usability identified that successful interfaces must integrate multiple information types - market data, social sentiment, security indicators - within unified presentation frameworks to reduce cognitive overhead and improve decision-making efficiency [24].

## 2.6 Research Gap and Theoretical Integration

Despite substantial research on cognitive load in trading contexts and the growing adoption of browser-based trading tools, significant gaps remain in understanding



how integrated overlay systems can address information fragmentation challenges specific to cryptocurrency trading environments. Existing literature on trading interface design focuses primarily on traditional financial markets or treats cryptocurrency trading as a simple extension of conventional trading practices, failing to address the unique cognitive demands created by social media integration and extreme information fragmentation.

Research examining user experience in cryptocurrency applications identifies fundamental cognitive challenges that remain unaddressed. Studies analyzing existing cryptocurrency trading platforms reveal that the primary task for UX optimization is the development of intuitive interfaces that reduce cognitive load on users. This involves implementing principles of cognitive ergonomics to create interfaces that naturally align with users' mental models, yet current research shows significant gaps in applying these principles to fragmented multi-platform cryptocurrency trading environments [25].

Current research on browser extensions for financial applications has emphasized security and performance considerations while giving insufficient attention to cognitive support capabilities and user experience optimization. Studies specifically examining cognitive load measurement methods for user interface evaluation reveal a critical need for comprehensive approaches to assess cognitive load in complex digital environments, yet limited research exists on applying these methods to cryptocurrency trading contexts where multiple information sources must be processed simultaneously [26].

The integration of social media sentiment analysis into trading decision support systems represents a particularly underexplored area, despite clear evidence of social media's influence on cryptocurrency price formation. Recent research on social media

integration in trading platforms demonstrates the feasibility of developing systems that combine real-time market data with social media analysis, yet these studies focus primarily on standalone applications rather than integrated browser-based overlay solutions that could reduce information fragmentation [27].

The present study addresses these research gaps by developing and empirically evaluating a theoretically grounded browser extension specifically designed to reduce cognitive load and improve task efficiency in fragmented cryptocurrency trading workflows. By integrating Cognitive Load Theory with practical interface design principles and empirical evaluation methods, this research contributes both theoretical understanding and practical solutions for the identified challenges in cryptocurrency trading environments.

In summary, literature review reveals five interconnected challenge categories that collectively justify the need for integrated cognitive support systems in cryptocurrency trading environments, as summarized in Table 1.

Challenge Category	Primary Issues	Impact on Traders
Information Fragmentation	Multiple platform switching; Context-switching costs; Manual information synthesis	Reduced decision accuracy; Increased cognitive overhead; Task-switching penalties
Security Vulnerabilities	5.17% malicious extension rate; \$1M+ financial losses; Phishing attacks on wallets	Financial risk; Trust concerns; Platform abandonment
Performance Degradation	Browser extension latency; Energy consumption impact; Resource overhead	Delayed execution; System slowdowns; Reduced trading efficiency

Cognitive Load Overload	Information paradox; Working memory saturation; Excessive information display	Decreased decision-making efficiency; Performance degradation; Mental fatigue
Interface Design Limitations	Traditional HCI paradigms; Lack of cognitive support; Fragmented user experience	Suboptimal workflows; Increased learning curve; Reduced usability

*Table 1 Summary of interconnected challenges in implementing cognitive support systems in cryptocurrency trading environments*

## 3 System Design and Implementation

### 3.1 Overview

This chapter presents the technical design and implementation details of the Integrated Cryptocurrency Trading Overlay (ICTO) browser extension. The system was developed to address the profound issues of information fragmentation and cognitive overload prevalent in cryptocurrency trading, integrating real-time market data, social media signals, and security analytics directly into user workflows on platforms such as Twitter/X, Discord, and Telegram. As identified in the literature review, cryptocurrency traders face substantial cognitive demands from processing multiple information sources across fragmented platforms, with task-switching costs significantly reducing decision accuracy [7], [8], [12]. This system addresses the research gap where browser-based trading tools emphasize security and performance while neglecting cognitive support capabilities [25]. The ICTO design specifically targets the information fragmentation challenges that create cognitive overload in cryptocurrency trading environments. The following sections detail the architecture, implementation approach, user interface components, and performance characteristics of the system.

### 3.2 Overlay User Interface and Feature Set

The ICTO interface serves as the primary interaction point for users during trading workflows, providing consolidated access to market data, security analytics, and trading functionality within a single, context-aware panel. The interface design prioritizes information density while maintaining cognitive accessibility through strategic visual hierarchy and progressive disclosure.

### 3.2.1 Primary Interface Components

Figure 1 illustrates the main overlay interface displaying comprehensive token information for active trading decisions.

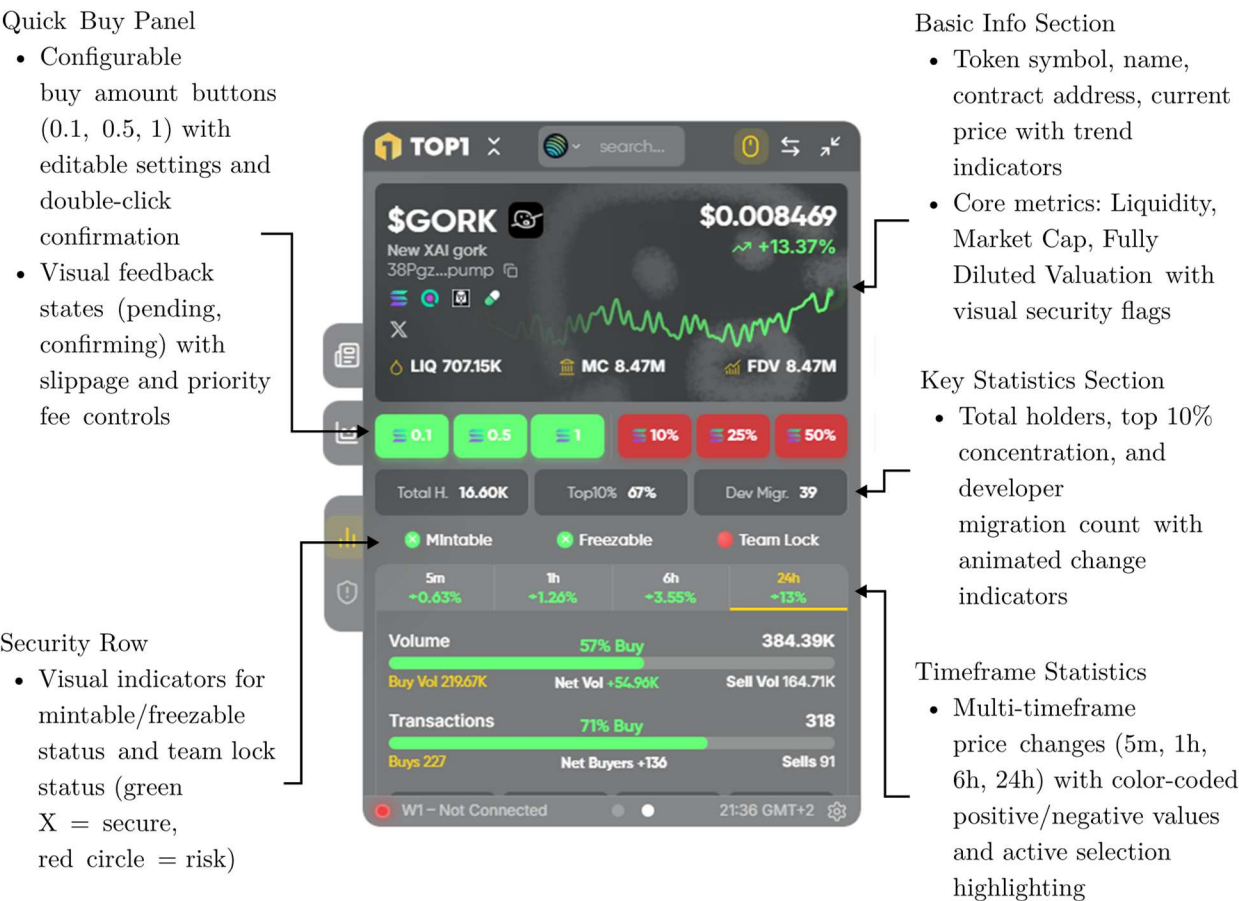


Figure 2: Main overlay interface showing token details, integrated price chart, and quick-action trading buttons.

The interface header contains the token symbol, current price, and percentage change with color-coded indicators for immediate trend recognition. Below this, key financial metrics including liquidity (LIQ), market capitalization (MC), and fully diluted valuation (FDV) provide essential valuation context. The integrated price chart displays real-time price movements with technical indicators, enabling rapid technical

analysis without requiring navigation to external charting platforms. Quick-action buttons provide immediate access to common trading operations with position sizing options (0.1, 0.5, 1 SOL) and risk management controls (10%, 25%, 50% position sizes). This information hierarchy follows established HCI principles for high-stakes decision-making environments, where critical data must be immediately accessible to reduce cognitive search time and working memory demands [26].

### 3.2.2 Automatic Token Detection and Social Media

Figure 2 demonstrates the overlay’s integration within social media workflows, specifically showing operation alongside Twitter/X content. The overlay maintains persistent positioning while users consume social media content, enabling seamless information gathering without disrupting existing browsing patterns.

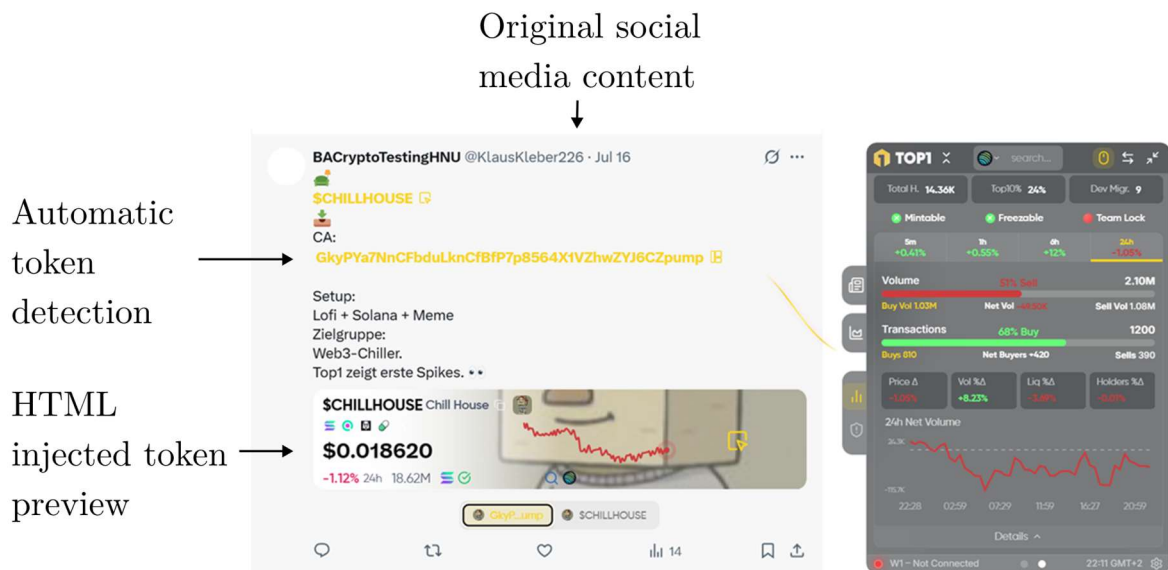


Figure 3: Overlay integration with Twitter/X, showing contextual token information alongside social media content.

A key enabling feature of this integration is the automatic token detection capability: the system continuously scans the visible content for Solana (SOL) token contract

addresses and ticker symbols in real time. Detected tokens are immediately parsed, validated, and linked to the overlay, triggering pre-fetching of market and security data. This eliminates the need for users to manually highlight, copy, or search for token addresses - substantially reducing interaction steps and click counts during high-tempo trading sessions. Token information updates automatically based on detected content, providing contextual data relevant to current social media discussions without any manual input. This automation directly addresses what Cognitive Load Theory identifies as extraneous cognitive load - mental effort imposed by poor interface design rather than task complexity itself [11]. By reducing manual interaction steps, the system minimizes task-switching costs that research shows significantly impair trading performance [11].

### 3.2.3 Extended Analytics View

The overlay supports expanded analytical capabilities through progressive disclosure mechanisms. Figure 3 shows the extended interface providing detailed trading statistics including holder analytics, volume breakdowns, and transaction patterns. Key security indicators (Mintable, Freezable, Team Lock) provide immediate risk assessment, while temporal price performance across multiple timeframes (5m, 1h, 6h, 24h) supports both scalping and swing trading strategies.

Trading volume analysis includes buyer/seller ratios and net position changes, providing insight into market sentiment and liquidity depth. The 24-hour net volume chart enables trend identification and momentum analysis within the overlay interface.



Figure 4: Extended overlay view with detailed trading statistics, security indicators, and multi-timeframe price performance.

### 3.2.4 Advanced Security and Network Analysis

Figure 4 illustrates the overlay's comprehensive security analysis capabilities, which proved essential during experimental tasks requiring risk assessment and token evaluation. The Security & Network Analysis module consolidates multiple risk indicators into a unified interface, displaying security warnings with validation status, insider network analysis showing network size and volume distribution, and detailed top holder breakdowns with ownership concentration metrics.



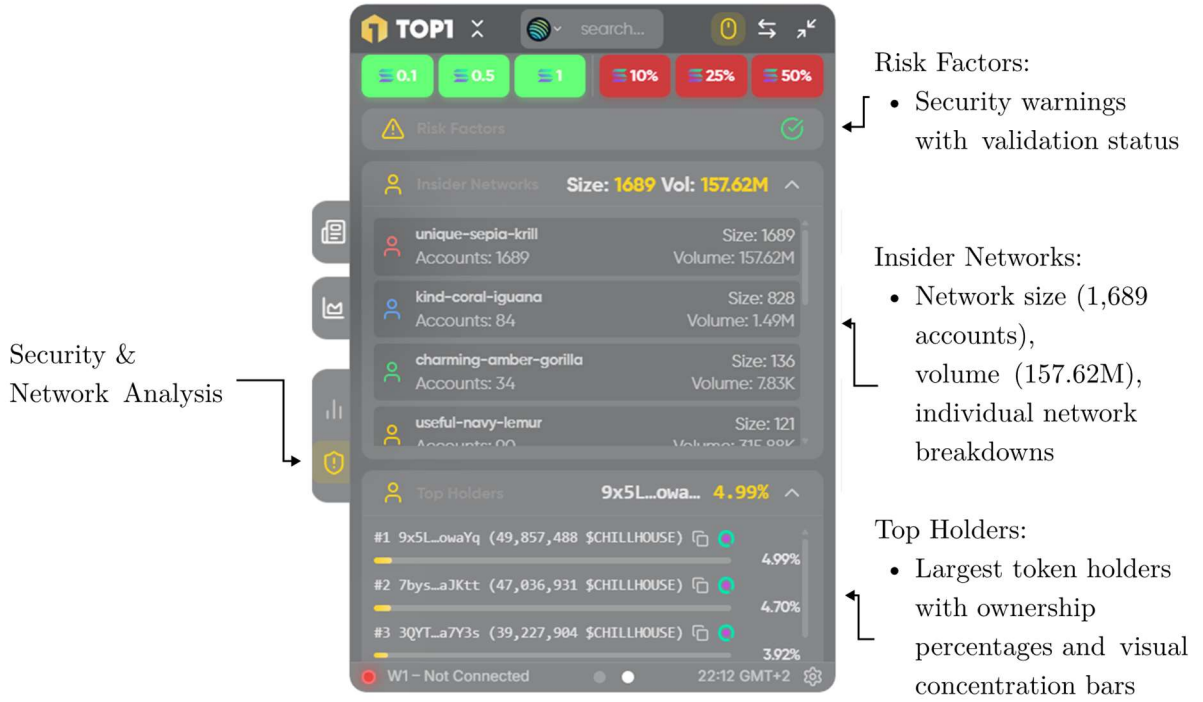


Figure 5: Security & Network Analysis module showing risk factor validation indicators, insider network size and volume metrics, individual network breakdowns, and top holder concentration analysis with ownership percentages.

This advanced analytical view enables rapid security assessment without requiring navigation to multiple external tools. During experimental sessions, participants could access detailed insider network breakdowns, identify potential concentration risks through top holder analysis, and evaluate security factors through integrated validation indicators. The visual hierarchy prioritizes critical risk factors while providing progressive disclosure of detailed network analytics, supporting both quick screening and comprehensive due diligence workflows.

### 3.2.5 Search and Discovery Features

Figure 5 illustrates the overlay's search and comparison functionality, enabling users to query multiple tokens simultaneously. The search interface supports both symbol and contract address lookup, with results displayed in a streamlined format showing

key metrics for rapid comparison. This functionality proves essential during experimental tasks requiring token identification and analysis across multiple assets.

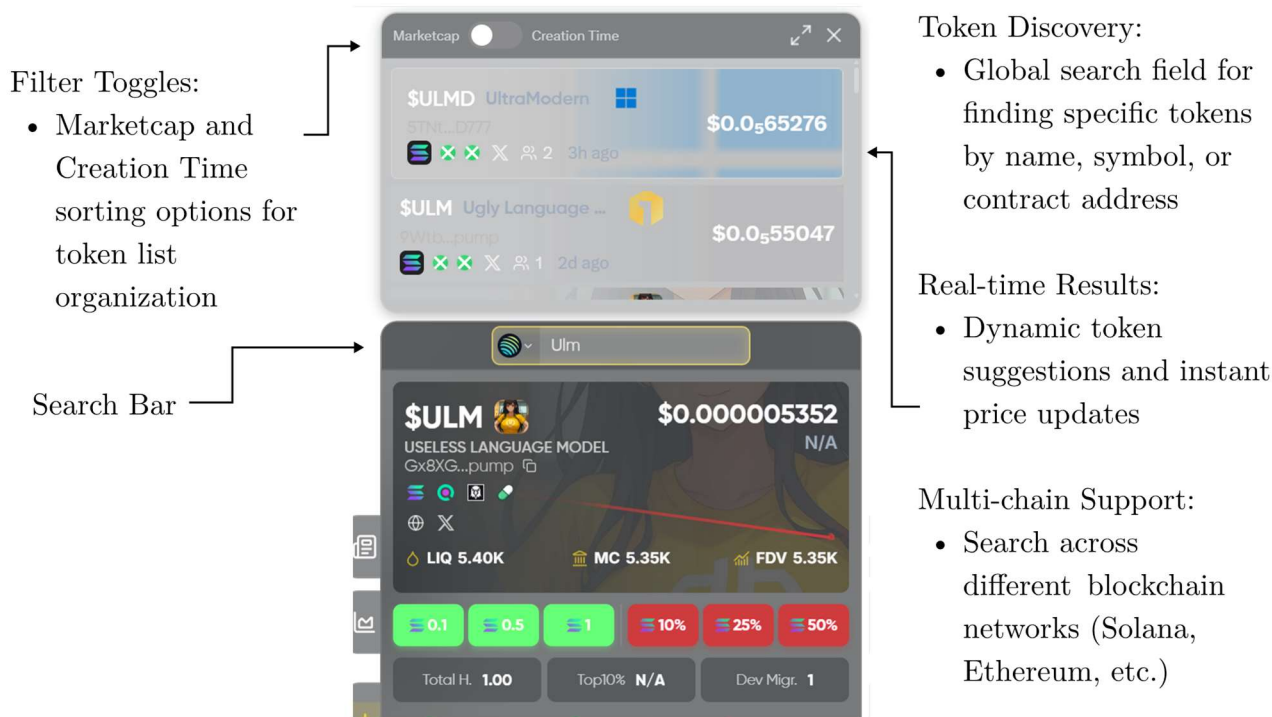


Figure 6: Search interface and token comparison features, showing multi-token lookup capabilities and search result presentation.

### 3.2.6 Workflow Integration and Context Preservation

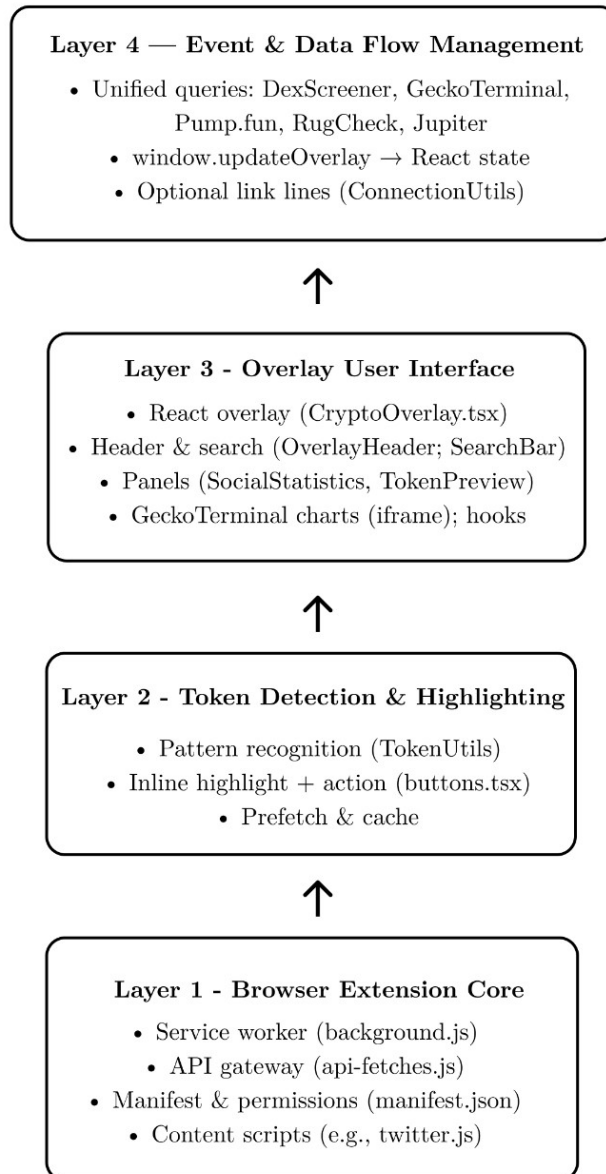
The overlay design maintains strict adherence to workflow preservation principles, ensuring that users never lose context or position within their primary browsing activities. All overlay interactions operate through hover states and click actions that avoid modal dialogs or forced navigation. The draggable interface allows optimal positioning relative to source content, while resize controls accommodate different screen configurations and information density preferences.

Connection indicators (shown as connecting lines in some configurations) visually link detected tokens within social media content to their corresponding overlay information, providing clear spatial relationships between source content and

analytical data. This visual connection reduces cognitive overhead associated with context switching, addressing research findings that demonstrate significant performance degradation when traders must process information across multiple fragmented sources [6], [7], [12].

### 3.3 Four-Layer Architecture Design

The ICTO system employs a modular four-layer architecture that separates concerns while maintaining efficient data flow and user interaction capabilities. This modular separation addresses the cognitive support gap identified in existing browser-based trading tools by providing dedicated layers for information aggregation and user interface optimization [12], [24].



*Figure 7: ICTO system architecture, illustrating the four-layer modular framework for browser-based integration and real-time data aggregation.*

### 3.3.1 Layer 1: Browser Extension Core

The foundation layer consists of a service worker that manages extension lifecycle events, scheduled tasks, and inter-component communication through Chrome's messaging API. This layer implements context menus and keyboard shortcuts for

quick-access functionality, enabling users to trigger overlay features through familiar interaction patterns. The API management layer handles asynchronous communication with external data sources, implementing performance timing, retry logic, and timeout handling to ensure reliable data retrieval under varying network conditions.

Content script registration dynamically loads platform-specific scripts based on the current web page context. For instance, `twitter.js` loads specifically when users navigate to Twitter/X, while `cryptooverlay.js` manages the overlay rendering functionality across all supported platforms. This approach ensures optimal performance by loading only necessary code components while maintaining extensibility for future platform support.

### 3.3.2 Layer 2: Token Detection and Highlighting

The token detection layer continuously monitors page content for cryptocurrency addresses and ticker symbols using pattern recognition algorithms implemented in the `TokenUtils` module. When tokens are identified, the system injects interactive elements through `buttons.tsx`, which wraps detected tokens with styled HTML spans and attaches action buttons that enable immediate information retrieval.

Proactive metadata prefetching optimizes user experience by retrieving and caching token information for newly encountered assets, reducing response latency when users interact with highlighted elements. This prefetching strategy balances performance optimization with resource management, prioritizing recently detected tokens while maintaining reasonable cache sizes.

### 3.3.3 Layer 3: Overlay User Interface

The overlay interface (`CryptoOverlay.tsx`) provides the primary user interaction surface through a draggable and resizable React-based component system. The interface maintains persistent positioning across browser sessions and supports two primary view modes: Trading and Stats screens, each optimized for different user workflows and information requirements.

Component architecture follows React best practices with modular, reusable elements including `OverlayHeader.tsx` for navigation and controls, `SearchBar.tsx` with `ExtendedSearchResults.tsx` for multi-platform token search functionality, and specialized information panels (`BasicInfo.tsx`, `KeyStatsSummary.tsx`, `SecurityStatistics.tsx`, `SocialStatistics.tsx`) that present contextually relevant data.

Chart integration utilizes lazy-loaded GeckoTerminal price charts embedded through `iframe` components, supporting dynamic resizing and real-time updates. State management employs React hooks for local component state while maintaining centralized data flow for cross-component communication and consistency.

### 3.3.4 Layer 4: Event and Data Flow Management

The data flow layer orchestrates user interactions with external API integration through a centralized event handling system. User actions - including token button clicks, search queries, and automatic token detection - trigger unified API queries that aggregate information from multiple external services including DexScreener, GeckoTerminal, Pump.fun, RugCheck, and Jupiter.

Real-time updates propagate through the `window.updateOverlay` function, which pushes aggregated data into the React state management system, triggering

immediate interface updates without requiring manual refresh or navigation. Optional visual connection features utilize `ConnectionUtils` to draw dynamic lines between highlighted tokens and overlay positions, providing intuitive visual associations for users.

### 3.4 External API Integration

The system integrates with five primary external data sources to provide comprehensive cryptocurrency information:

- DexScreener: Real-time price data, trading volume, and liquidity metrics
- GeckoTerminal: Historical price charts and market analysis data
- Pump.fun: Token launch and trending information specific to meme coins
- RugCheck: Security analysis and risk assessment for token contracts
- Jupiter: Solana ecosystem trading data and token swap information

Application Programming Interface (API) integration employs asynchronous request patterns with comprehensive error handling, including exponential backoff retry logic, timeout management, and graceful degradation when specific services become unavailable. Performance monitoring tracks response times and success rates to identify potential optimization opportunities and service reliability issues. This multi-source integration addresses the fragmentation challenge where traders typically navigate between separate platforms to access DexScreener, GeckoTerminal, Pump.fun, RugCheck, and Jupiter data [21].

## 3.5 User Interface Design Principles

### 3.5.1 Cognitive Load Reduction Through Design

Interface design prioritized cognitive load reduction through strategic information hierarchy and progressive disclosure principles. Primary information elements (price, market capitalization, volume) receive prominent visual treatment, while secondary data are accessible through progressive disclosure mechanisms that avoid overwhelming users with excessive information density.

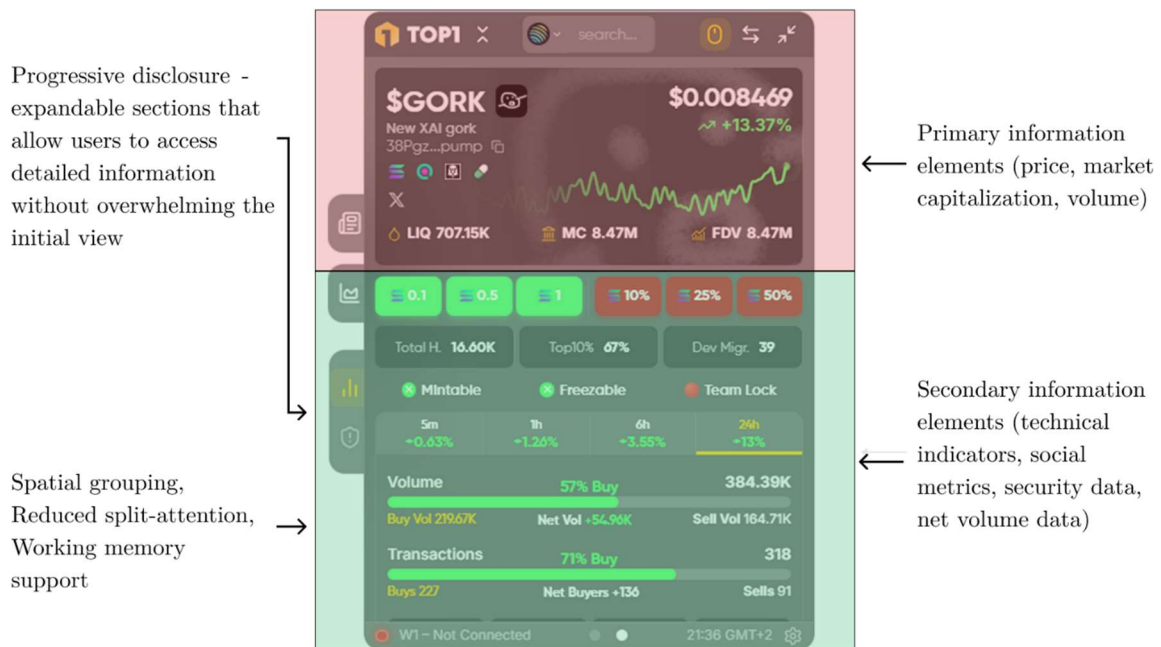


Figure 8: ICTO overlay interface demonstrating cognitive load reduction through integrated information architecture. Primary information elements (price, market capitalization, volume) are prominently displayed in the upper section, while secondary information elements (technical indicators, social metrics, security data, transaction data) are systematically organized below.

Color coding and visual indicators provide immediate signal recognition, with green/red conventions for price movements, warning indicators for security risks, and engagement metrics displayed through intuitive graphical elements. Typography



hierarchy ensures rapid scanning capabilities, with consistent font sizes and weights that support quick information processing under time pressure.

This approach directly implements Cognitive Load Theory recommendations for complex interface design, where primary information receives prominent treatment while secondary data remain accessible without overwhelming working memory capacity. Research demonstrates that reducing extraneous cognitive load through strategic information hierarchy significantly improves trading performance in high-frequency environments [22], [24], [27], [29].

### 3.5.2 Workflow Integration Strategy

The overlay design maintains compatibility with existing user workflows by avoiding modal dialogs or navigation disruption. The draggable interface allows users to position information panels optimally relative to their primary content consumption, while resizing capabilities accommodate different screen configurations and user preferences.

Context preservation ensures that overlay interactions never interrupt ongoing social media consumption or trading activities. Users can access detailed token information, execute searches, and review analytics without losing their position in social media feeds or requiring navigation to external websites.

## 3.6 Performance Optimization and Scalability

### 3.6.1 Response Time Optimization

Given research findings that browser extensions can introduce latency of up to several seconds [17], our own internal benchmarks measured an average response time of 285 ms ( $\sigma = 60$  ms) for token data retrieval under typical market conditions. This level of performance exceeds the sub-second requirement necessary for high-tempo

trading workflows. Caching strategies reduce repeat query latency by up to 90% for frequently accessed tokens, while intelligent prefetching anticipates user information needs based on page content analysis.

Memory management employs efficient garbage collection patterns and component lifecycle optimization to minimize browser resource consumption. The extension maintains minimal background processing overhead when not actively in use, preserving overall browser performance and user experience.

### 3.6.2 Scalability Considerations

The modular architecture supports extensibility to additional cryptocurrency platforms and trading environments. Content script patterns enable straightforward adaptation to new websites, while the API abstraction layer accommodates integration with additional data sources without requiring core functionality modifications.

Database integration through Supabase provides scalable data storage and retrieval for user interaction logging, system analytics, and feature usage metrics. This infrastructure supports research data collection while maintaining user privacy and data protection compliance.

## 3.7 Security and Privacy Implementation

Security implementation follows browser extension best practices with minimal permission requirements and sandboxed execution environments. User data handling complies with General Data Protection Regulation (GDPR) requirements through explicit consent mechanisms and transparent data usage policies.

API communications employ secure HTTPS protocols with API key management that prevents credential exposure in client-side code. Transaction preview and trading

simulation features operate in isolated environments that prevent unauthorized access to user funds or trading accounts.

### 3.8 Development and Testing Framework

System development employed iterative testing with cryptocurrency traders throughout the design process, ensuring interface elements and workflow patterns aligned with authentic trading requirements. Cross-browser compatibility testing confirmed functionality across Chrome, Edge, and other Chromium-based browsers.

Performance benchmarking established baseline metrics for response times, memory usage, and API reliability under various network conditions. User acceptance testing with domain experts validated interface usability and identified optimization opportunities that informed final implementation decisions.

This iterative approach ensured the system effectively addresses the cognitive load challenges identified in the literature review, particularly around information fragmentation and task-switching costs

## 4 Methodology

### 4.1 Research Design

This study used a within-subjects design to sensitively detect *User Interface* (UI) driven changes in cognitive load and task efficiency, with each of the 15 participants completing trading tasks under both standard browser workflows and the ICTO extension. A within-subjects approach controls for individual differences in trading experience and technical proficiency, increasing statistical power by reducing error variance associated with between-subjects comparisons. Counterbalancing the order of conditions prevented learning and fatigue effects from biasing results. According to established power analysis guidelines, within-subjects designs with 12–20 participants are sufficient to detect medium to large effect sizes ( $d \geq .50$ ) with power  $\geq .80$  at  $\alpha = .05$  [28].

### 4.2 Participants

Fifteen active cryptocurrency traders were recruited via professional networks within the cryptocurrency community. All participants were male, aged 18-35, with at least six months of active trading experience, familiarity with Solana ecosystem tokens, and regular use of social media for trading information. This demographic profile aligns with research showing that social media-driven cryptocurrency trading is dominated by young males, with studies indicating that 43% of US males aged 18-29 have used cryptocurrency, and that over 85% of meme coin content engagement on social platforms comes from users aged 18-34.

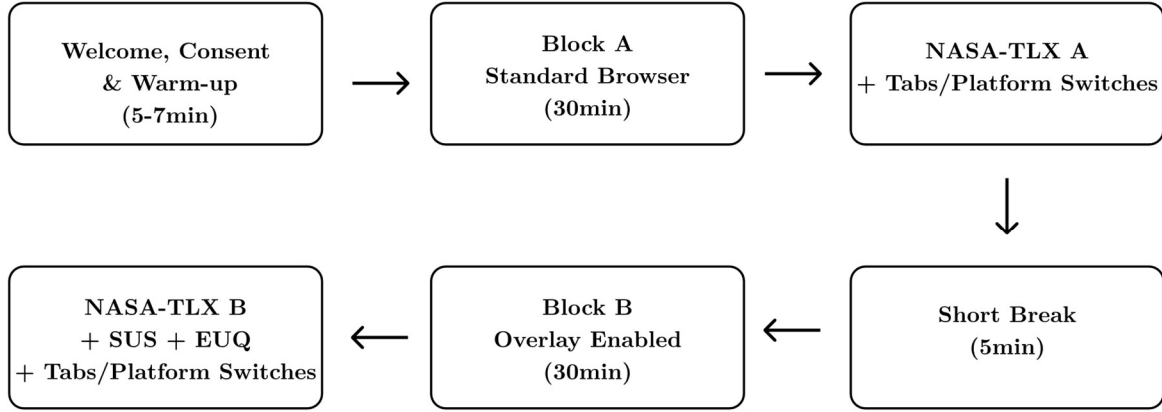
Additional inclusion criteria required experience with decentralized exchange

interfaces and proficiency in browser-based trading tools. Technical requirements included a computer with microphone and video capabilities and stable internet connectivity to ensure reliable session recording and communication. Purposive sampling ensured the sample represented the target user population. The sample size of fifteen aligns with HCI usability guidelines recommending five to twelve users to detect major usability issues in interface evaluations [29]. The gender homogeneity of the sample limits generalizability to the broader trading population and is acknowledged as a study limitation [29].

## 4.3 Session Procedure and Tasks

### 4.3.1 Session Procedure

All experimental sessions took place remotely, with participants working on their own computers to maximize ecological validity and closely mirror real-world trading conditions. At the start of each session, participants received a welcome, provided informed consent, and completed a brief pre-experiment interview covering demographics and trading experience. The experimental protocol comprised two main blocks, presented in counterbalanced order to control for learning and fatigue effects, as illustrated in Figure 9.



Order counterbalanced (A→B vs. B→A). Metrics recorded per block.

*Figure 9: Experimental session structure, showing the counterbalanced protocol with sequential browser and overlay conditions, break, and metrics collection.*

In Block A, participants performed the assigned tasks using their standard browser setup and any information sources or tools of their choice (e.g., DexScreeners, Jupiter, RugCheck). In Block B, they completed the same tasks with the ICTO overlay enabled, allowing them to access all required information via an integrated extension interface. Each block lasted for a maximum of thirty minutes and was separated by a standardized five-minute break to minimize carryover and cognitive fatigue.

Upon completing each block, participants rated their perceived cognitive workload using the NASA Task Load Index (NASA-TLX) [30]. After the overlay block, additional usability and user experience data were collected using the System Usability Scale (SUS) and the User Experience Questionnaire (UEQ). The number of browser tabs and platforms used during each block was recorded as an objective measure of workflow fragmentation. Technical issues were addressed through a pause-and-resume protocol, and any interruptions were documented to safeguard the integrity of collected data[32], [33].

### 4.3.2 Tasks

Within both experimental blocks, participants completed two sequential trading tasks designed to realistically reflect common information synthesis challenges in cryptocurrency trading. For both tasks, participants worked from a standardized Twitter feed presented via a dedicated test account ([x.com/KlausKleber226](https://x.com/KlausKleber226)). This curated feed consisted of 46 tweets, referencing a total of 58 token tickers and 16 token addresses. The use of this controlled social media stream ensured that all participants encountered identical informational content, closely simulating authentic trading scenarios while facilitating experimental consistency. This approach is well-established in both HCI and cognitive workload research [26].

Aspect	Task 1: Token Analysis	Task 2: Trading Workflow
Objective	Identify and analyze token addresses chronologically	Locate and execute a simulated trade on the first token meeting all predefined criteria
Data Points	Number of tokens identified and documented	Token's holder count, 24h price change, security status
Success Criteria	Document findings for each token	Identification and simulated trade of a token with: >1,000 holders, >10% price increase (24h), and no security risks
Information Source	Twitter feed (chronological order)	Twitter feed (systematic review)
Completion	When 30 minutes elapsed or the Twitter feed was exhausted	When 30 minutes elapsed or after completing the trade simulation

*Table 2 Task Overview for both Blocks.*

Task 1 required participants to review the feed in chronological order, identifying and analyzing token addresses as they appeared. For every token encountered, participants were instructed to document pertinent details, including basic token information, security risks, market capitalization, liquidity, and current price.

For Task 2, participants systematically analyzed the same set of tweets to identify the first token that satisfied all predefined criteria: specifically, the token needed to have more than 1,000 holders, demonstrate a price increase of at least 10% over the previous 24 hours, and show no observable security risks. Upon finding a qualifying token, participants simulated the process of executing a 1 SOL trade, carrying the workflow up to but not including the final transaction confirmation.

Both tasks were constrained to a maximum of thirty minutes or until their specified criteria were met. A full summary of the objectives, required data points, and success criteria for both tasks is provided in Table 2.

This experimental structure enabled rigorous, controlled comparison of workflow efficiency, cognitive load, and user experience between both conventional browser-based trading and the integrated overlay solution.

## 4.4 Statistical Analysis and Analytical Framework

Data from 15 participants were analyzed in a within-subjects, counterbalanced design to assess ICTO’s effects on cognitive load and information fragmentation. Key outcome metrics reflected the constructs defined in Chapter 2:

- Behavioral fragmentation (tab counts, platform switches, errors) reflected cognitive overhead from fragmented workflows.



- Performance and accuracy metrics (completion times, error rates, Task 1 coin count) measured efficiency gains and retrieval accuracy as extraneous load changed.
- Subjective experience was evaluated using NASA-TLX (cognitive workload, 0–10 scale, each block), and after the ICTO block, SUS (usability, 0–100) and UEQ (experience, 1–7).

All procedures followed ethical guidelines, with informed consent and GDPR-compliant data security.

#### 4.4.1 Data Collection

Manual logs of browser tabs and platform switches were cross-validated against timestamped screen recordings. Task times and error rates were extracted from video data. Questionnaires were administered immediately after each block.

#### 4.4.2 Data Preparation & Reliability

Block labels (A: browser, B: ICTO) were standardized. Time data were converted to minutes; counts and coin recognitions recorded as block totals. No sessions were excluded. Missing values were pairwise deleted; outliers flagged but retained. All scales demonstrated high reliability: SUS ( $\alpha = .915$ ), UEQ ( $\alpha = .886$ ), NASA-TLX ( $\alpha = .947$ ).

#### 4.4.3 Statistical Methods

Shapiro–Wilk tests assessed normality of the within-subject difference scores (B–A). If differences were approximately normal we used the paired-samples t-test (reporting Cohen’s  $d^z$ ); otherwise the Wilcoxon signed-rank test (rank-based  $|r|$ ). Holm adjustment controlled familywise error within each test family. Differences were

coded  $\Delta = B - A$  (ICTO minus baseline); negative  $\Delta/t/d^z$  indicate reductions with ICTO.

- **Efficiency:** Analysis of total/completion times and coin counts
- **Fragmentation:** Comparison of tab count, platform switches, and errors
- **Subjective differences:** Paired comparisons of NASA-TLX, SUS, and UEQ
- **Correlations:** Spearman's  $\rho$  with bootstrapped 95% CIs assessed associations between change scores (e.g.,  $\Delta$  NASA-TLX Effort vs.  $\Delta$  Time), Holm-corrected for multiple tests.

This analytical framework enabled robust evaluation of ICTO's effects on performance, accuracy, information fragmentation, and perceived workload.

#### 4.4.4 Hypotheses

The study tests the following hypotheses derived from the research framework:

- H1: ICTO reduces task completion time compared to the control condition.
- H2a: ICTO reduces tab count.
- H2b: ICTO reduces platform switches.
- H2c: ICTO reduces token identification errors.
- H4a–H4f: ICTO lowers NASA-TLX subscales (Mental, Physical, Temporal, Performance, Effort, Frustration).
- H5: ICTO improves usability and user experience, as measured by SUS and UEQ (descriptive benchmarking).

Each hypothesis is evaluated through paired-sample inferential tests (t-tests or Wilcoxon, depending on normality), with effect sizes reported (Cohen's  $d^z$  for paired-samples t-tests and rank-based  $|r|$  for Wilcoxon) and significance thresholds set at  $\alpha = 0.05$ .

## 5 Results

This chapter presents the empirical findings from the within-subjects experimental evaluation of the ICTO browser extension. Results are organized into performance outcomes, subjective assessments, and correlation analyses, providing comprehensive evidence for the system's impact on cryptocurrency trading workflows.

### 5.1 Performance Outcomes

All performance analyses compare the two experimental blocks within subjects, with Block A representing standard browser workflows and Block B representing ICTO-enabled workflows. Statistical comparisons employed paired tests with normality assessment and appropriate effect size calculations using Holm adjustment for multiple comparisons.

#### 5.1.1 Time-Based Performance

Across all 15 participants, total completion time decreased from  $M = 926.4$  s (15.4 min) in the baseline to  $M = 388.7$  s (6.5 min) with ICTO  $-58\%$ ,  $d^z = 1.64$ . Paired-samples t-test:  $t(14) = -6.34$ ,  $p_{\text{Holm}} = 5.51 \times 10^{-5}$ , Cohen's  $d^z = 1.64$ . Both Task 1 and Task 2 showed similarly large reductions (Task 1  $d^z = 1.52$ ; Task 2  $d^z = 1.46$ ; both  $p_{\text{Holm}} = 8.05 \times 10^{-5}$ ), indicating that the benefit generalizes from information lookup to analysis/synthesis workflows.

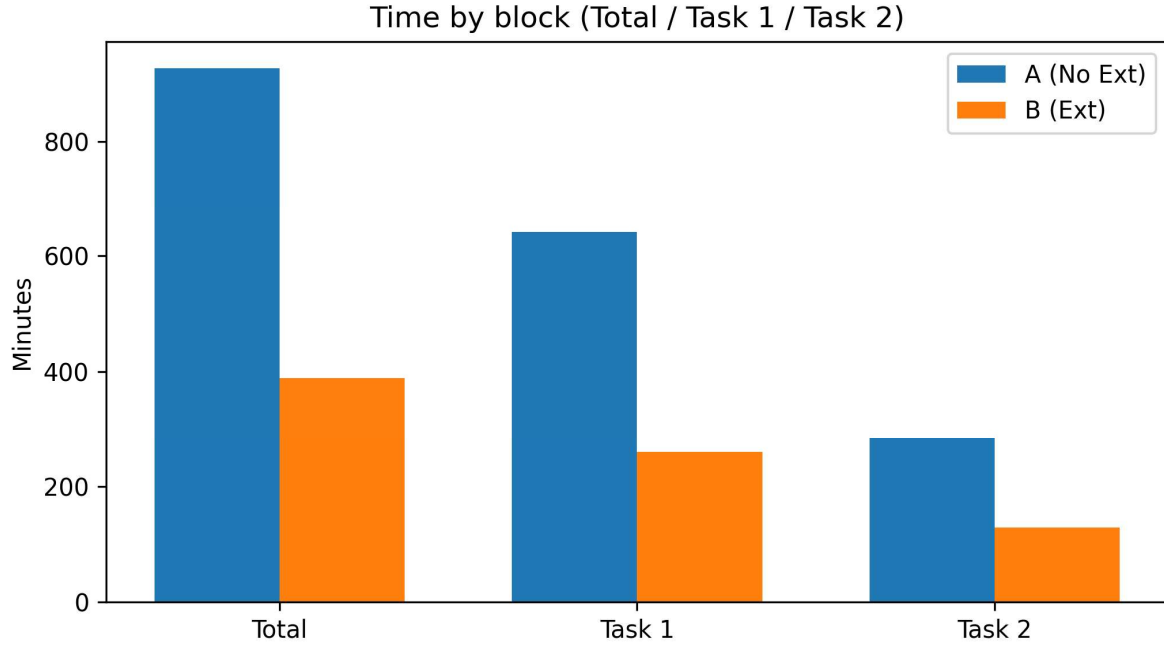


Figure 10: Time-based performance comparison showing total task time, Task 1 time, and Task 2 time (in minutes) across standard browser condition (A - No Ext) and ICTO condition (B - Ext).

As displayed in Figure 10, Task 1 completion was roughly twice as fast under the ICTO condition, while Task 2 also showed marked reduction in completion time. The consistent improvement across both tasks indicates that ICTO's benefits extend beyond simple information lookup to more complex analytical workflows requiring multiple information synthesis steps.

### 5.1.2 Behavioral Fragmentation Metrics

Behavioral indicators of cognitive fragmentation showed consistent improvements with the ICTO extension. Tab count, platform switches, and error count all demonstrated significant reductions when participants used the overlay system compared to standard browser workflows.

Error Count, Tab Count, Platform Switches — A vs B

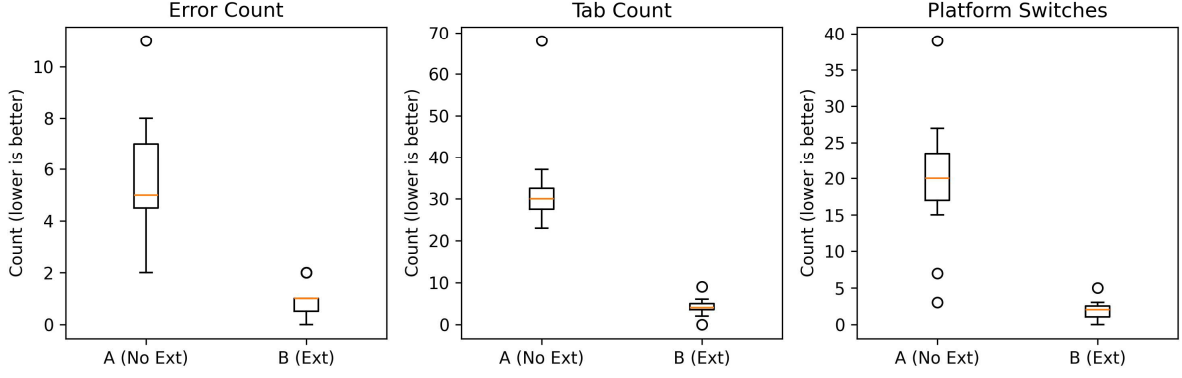


Figure 11: Error count, tab count, and platform switching frequency across standard browser condition (*A – No Ext*) and ICTO condition (*B – Ext*), visualized as boxplots.

Tab count decreased from  $M = 32.1$  ( $SD = 10.6$ ) in the standard condition to  $M = 4.3$  ( $SD = 2.0$ ) in the ICTO condition, representing an 87% reduction ( $t(14) = -9.79$ ,  $p_{\text{Holm}} = 3.65 \times 10^{-7}$ ,  $d^z = 2.53$ ). Platform switching frequency showed an even more dramatic improvement, decreasing from  $M = 19.8$  ( $SD = 8.3$ ) to  $M = 1.7$  ( $SD = 1.4$ ), a 91% reduction ( $t(14) = -8.51$ ,  $p_{\text{Holm}} = 6.64 \times 10^{-7}$ ,  $d^z = 2.20$ ). Error count decreased from  $M = 5.7$  ( $SD = 2.3$ ) to  $M = 0.9$  ( $SD = 0.6$ ), representing an 85% reduction in task execution failures ( $t(14) = -9.13$ ,  $p_{\text{Holm}} = 5.74 \times 10^{-7}$ ,  $d^z = 2.36$ ).

H2a (Tabs), H2b (Platform switches), and H2c (Errors): Supported. All three fragmentation indicators were significantly lower with ICTO (all  $p_{\text{Holm}} < .001$ ) with very large effects.

### 5.1.3 Task-Specific Accuracy

Token identification accuracy in Task 1 showed significant improvement with ICTO. Participants identified  $M = 13.0$  tokens ( $SD = 1.3$ ) in the standard browser condition compared to  $M = 16.0$  tokens ( $SD = 0.0$ ) in the ICTO condition. The ICTO

condition demonstrated a ceiling effect, with all participants achieving maximum possible accuracy in token identification from the standardized Twitter feed.

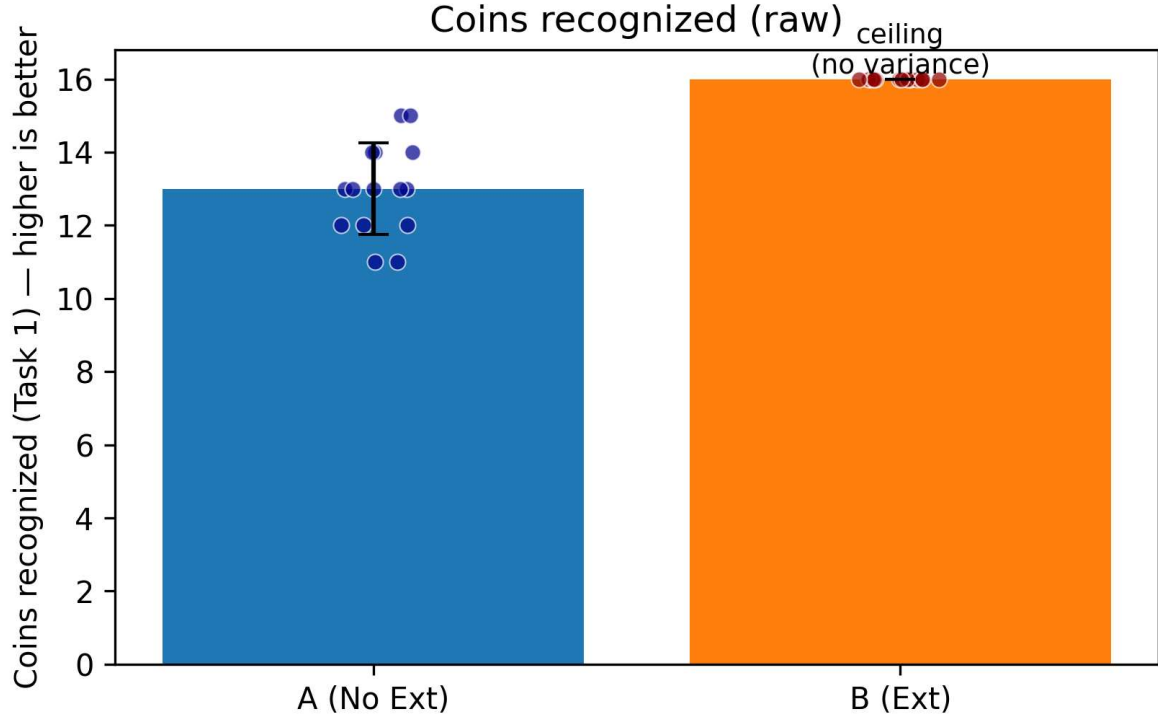


Figure 12: Token identification accuracy in Task 1 showing coins recognized (raw count) across conditions, with individual data points overlaid.

Wilcoxon signed-rank (exact):  $p = 6.1 \times 10^{-5}$ , rank-biserial  $r = 1.00$  (all participants improved). t-test for reference:  $t(14) = 9.27$ ,  $d^z = 2.39$

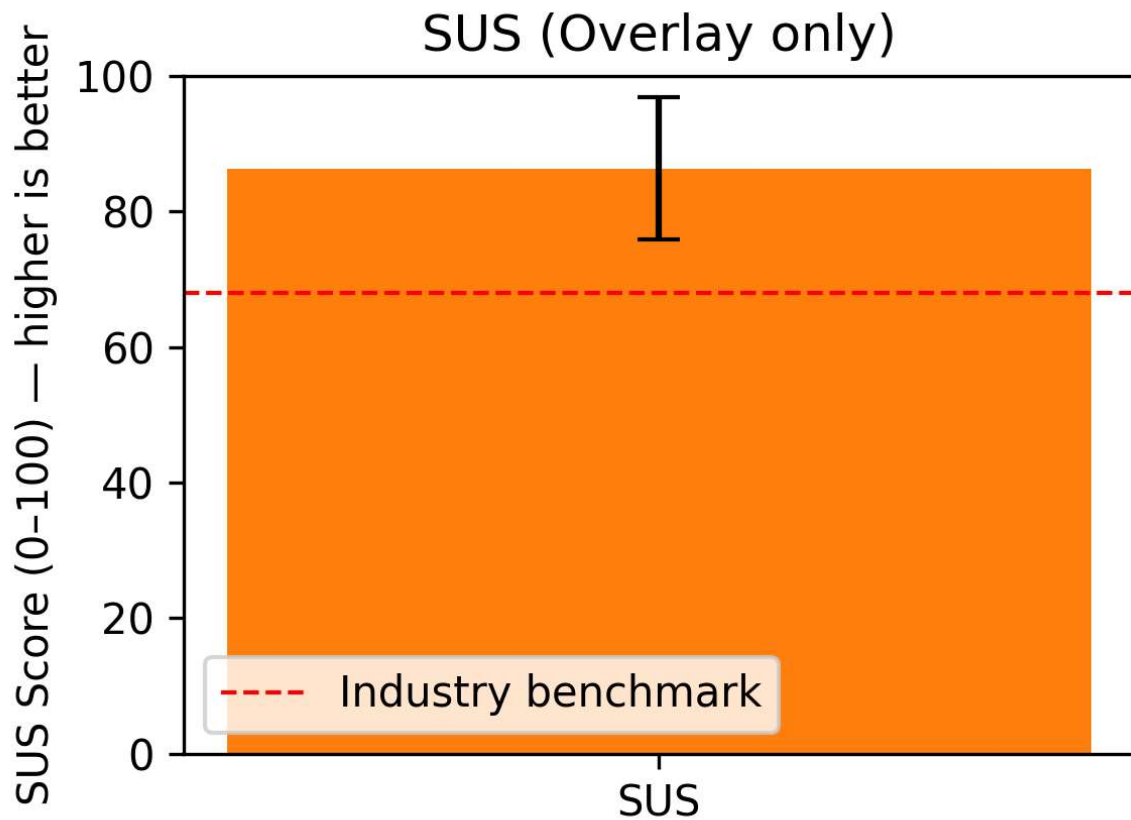
H3 (Task-1 accuracy): Supported. Participants recognized more tokens with ICTO (ceiling at  $M = 16.0$ ), indicating higher accuracy under the overlay.

## 5.2 Subjective Outcomes

Subjective evaluations comprised system-specific assessments collected exclusively after the ICTO condition and cognitive workload assessments collected after both experimental blocks. All subjective scales demonstrated excellent internal consistency reliability (SUS:  $\alpha = 0.915$ ; UEQ:  $\alpha = 0.886$ ; NASA-TLX:  $\alpha = 0.947$ ).

### 5.2.1 System Usability and User Experience

The System Usability Scale yielded a mean score of 86.3 (SD = 10.5) on the 0-100 scale, indicating excellent usability well above the established benchmark of 68 for digital systems.



*Figure 13: System Usability Scale (SUS) results for the ICTO condition showing mean score with 95% confidence interval on 0-100 scale, with red dashed reference line at 68 indicating industry benchmark for comparison.*

User Experience Questionnaire results across six dimensions showed consistently positive evaluations above the neutral midpoint on the 1-7 scale. Efficiency received the highest rating ( $M = 3.96$ ,  $SD = 0.56$ ), followed by Attractiveness ( $M = 3.92$ ,  $SD = 0.47$ ) and Novelty ( $M = 3.84$ ,  $SD = 0.95$ ). Dependability ( $M = 3.77$ ,  $SD = 0.95$ ), Perspicuity ( $M = 3.66$ ,  $SD = 0.87$ ), and Stimulation ( $M = 3.63$ ,  $SD = 0.72$ ) all



demonstrated favorable user perceptions of the overlay system's design and functionality.

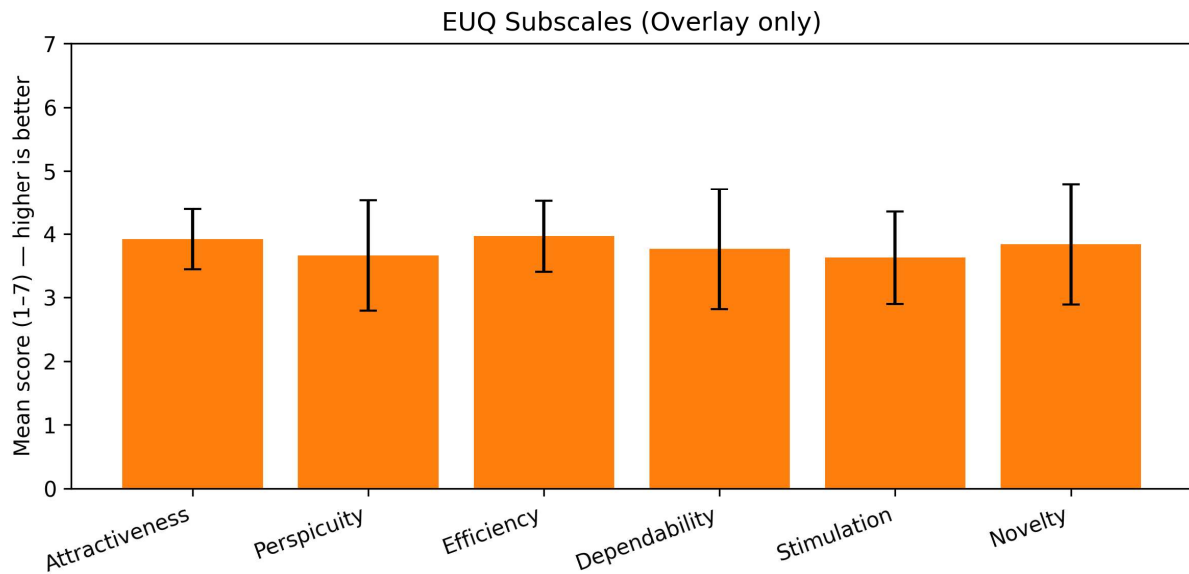


Figure 14: User Experience Questionnaire (UEQ) subscale scores for the ICTO condition (Block B – Ext), showing group means with 95% confidence intervals on a 1–7 scale.

### 5.2.2 Cognitive Workload Assessment

NASA-TLX analysis revealed substantial and statistically significant reductions in subjective cognitive workload across all relevant dimensions when using ICTO compared to standard browser workflows.

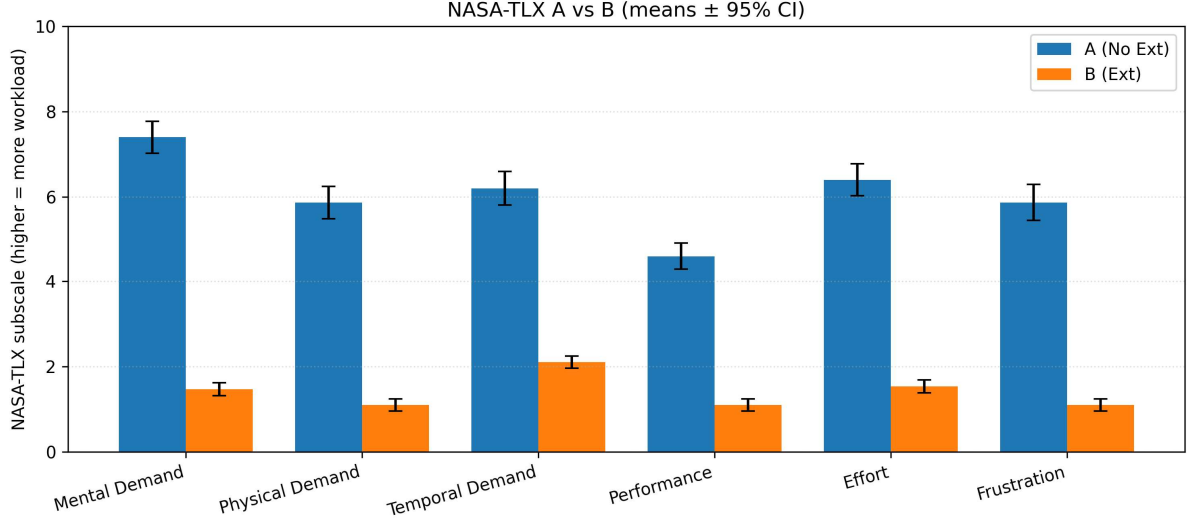


Figure 15: NASA-TLX subscale comparisons between standard browser condition (A – No Ext) and ICTO condition (B – Ext). Means with 95% confidence intervals are shown for all six workload dimensions (Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, Frustration).

Effort ratings showed substantial reductions, decreasing from  $M = 6.4$  ( $SD = 0.74$ ) to  $M = 1.5$  ( $SD = 0.30$ ), representing the most meaningful reduction in perceived work required ( $t(14) = -28.25$ ,  $d^z = 7.29$ ,  $p_{\text{Holm}} = 3.83 \times 10^{-13}$ ). This effort reduction proved to be the primary driver of performance improvements, as demonstrated by the strong correlation between effort changes and task efficiency gains (see Section 5.3.2).

Mental demand also decreased significantly, from  $M = 7.4$  ( $SD = 0.74$ ) to  $M = 1.5$  ( $SD = 0.30$ ) ( $t(14) = -36.89$ ,  $d^z = 9.52$ ,  $p_{\text{Holm}} = 1.43 \times 10^{-14}$ ).

Temporal demand decreased from  $M = 6.2$  ( $SD = 0.77$ ) to  $M = 2.1$  ( $SD = 0.28$ ), indicating significantly reduced time pressure ( $t(14) = -20.88$ ,  $d^z = 5.39$ ,  $p_{\text{Holm}} = 6.01 \times 10^{-12}$ ). Frustration levels decreased dramatically from  $M = 5.9$  ( $SD = 0.83$ ) to  $M = 1.1$  ( $SD = 0.28$ ), demonstrating reduced stress during trading workflows ( $t(14) = -27.23$ ,  $d^z = 7.03$ ,  $p_{\text{Holm}} = 4.75 \times 10^{-13}$ ).

Performance self-ratings improved from  $M = 4.6$  ( $SD = 0.63$ ) to  $M = 1.1$  ( $SD = 0.28$ ), with lower scores indicating better perceived performance ( $t(14) = -23.91$ ,  $d^z = 6.17$ ,  $p_{\text{Holm}} = 1.89 \times 10^{-12}$ ). Physical demand decreased from  $M = 5.9$  ( $SD = 0.74$ ) to  $M = 1.1$  ( $SD = 0.28$ ) ( $t(14) = -29.63$ ,  $d^z = 7.65$ ,  $p_{\text{Holm}} = 2.47 \times 10^{-13}$ ).

H4a–H4f (NASA-TLX subscales): Supported. All workload dimensions were significantly lower with ICTO after Holm correction.

### 5.3 Correlation findings

Correlation analysis examined relationships between subjective measures and objective performance using Spearman's rank correlations with bootstrap confidence intervals and Holm adjustment for multiple testing.

#### 5.3.1 Within-Block Relationships

Analysis of relationships within the ICTO condition revealed generally weak and non-significant correlations between subjective measures and objective performance indicators.

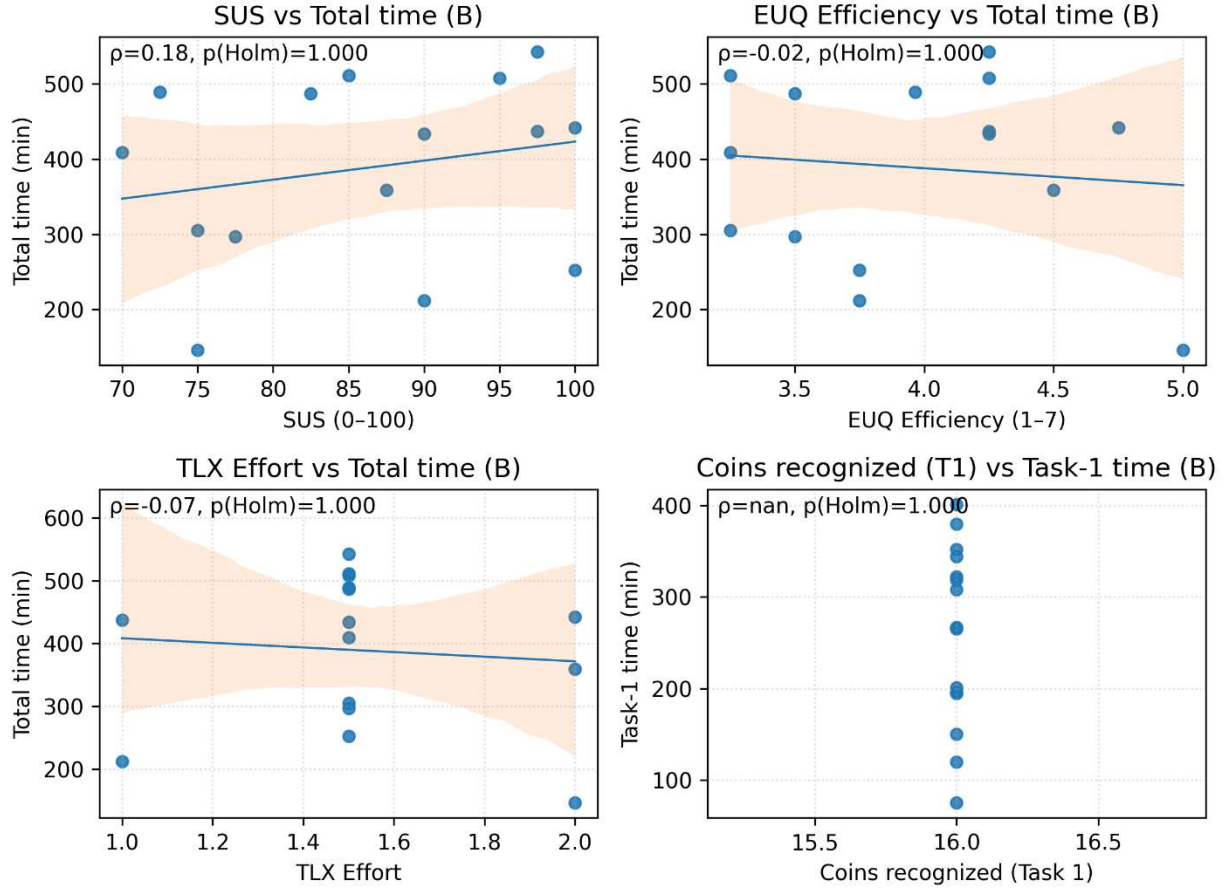


Figure 16: Correlations of within-subject change scores ( $\Delta = B - A$ ) for key variables, shown as scatterplots with regression overlays and 95% bootstrap confidence intervals. Panels illustrate relationships between  $\Delta$  Effort and  $\Delta$  Total time,  $\Delta$  Mental and  $\Delta$  Total time,  $\Delta$  Effort and  $\Delta$  Errors, and  $\Delta$  Effort and  $\Delta$  Platform Switches.

SUS scores showed a weak positive correlation with total task time ( $\rho = 0.18$ , 95% CI  $[-0.35, 0.68]$ ,  $p = 1.0$  after Holm adjustment), suggesting no meaningful relationship between perceived usability and objective performance. UEQ Efficiency ratings showed minimal correlation with total time ( $\rho = -0.02$ , 95% CI  $[-0.57, 0.55]$ ,  $p = 1.0$ ). TLX Effort scores demonstrated weak negative correlation with total completion time ( $\rho = -0.07$ , 95% CI  $[-0.60, 0.54]$ ,  $p = 1.0$ ). The relationship between coins recognized in Task 1 and Task 1 completion time could not be

computed due to the ceiling effect in the ICTO condition.

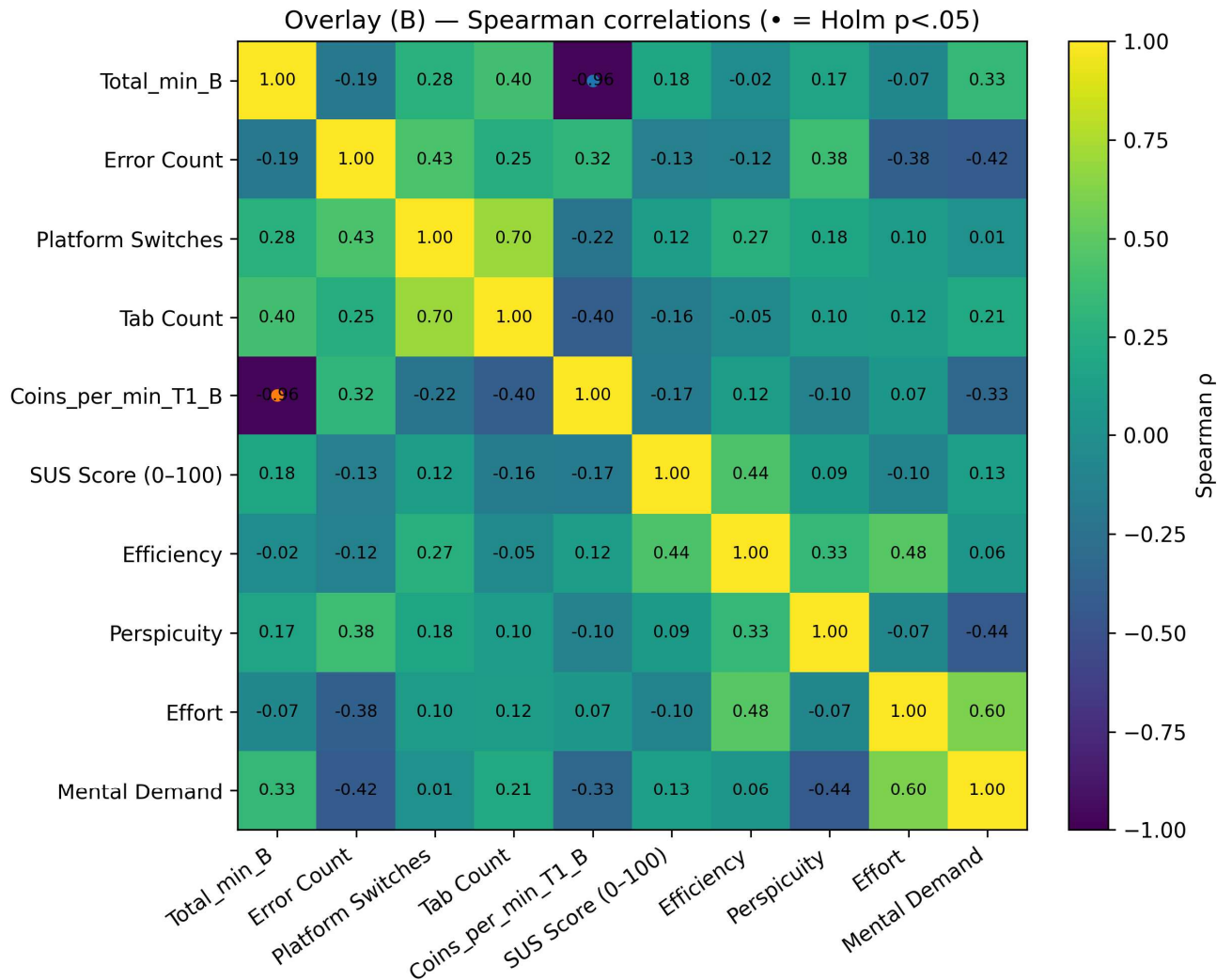


Figure 17: Heatmap of Spearman correlations for subjective and objective variables within the ICTO overlay condition (Block B). Filled dots mark correlations that are Holm-significant, illustrating the relationships among usability, workload, performance, and behavioral metrics when using the ICTO system.

### 5.3.2 Within-Subject Change Relationships

Analysis of within-subject changes revealed that effort reduction served as the primary mediator between ICTO usage and performance improvements. The correlation between effort reduction and time improvement showed a strong negative

relationship ( $\rho = -0.70$ , 95% CI  $[-0.94, -0.22]$ ,  $p = 0.015$  after Holm adjustment), confirming effort as the key psychological mechanism driving efficiency gains.

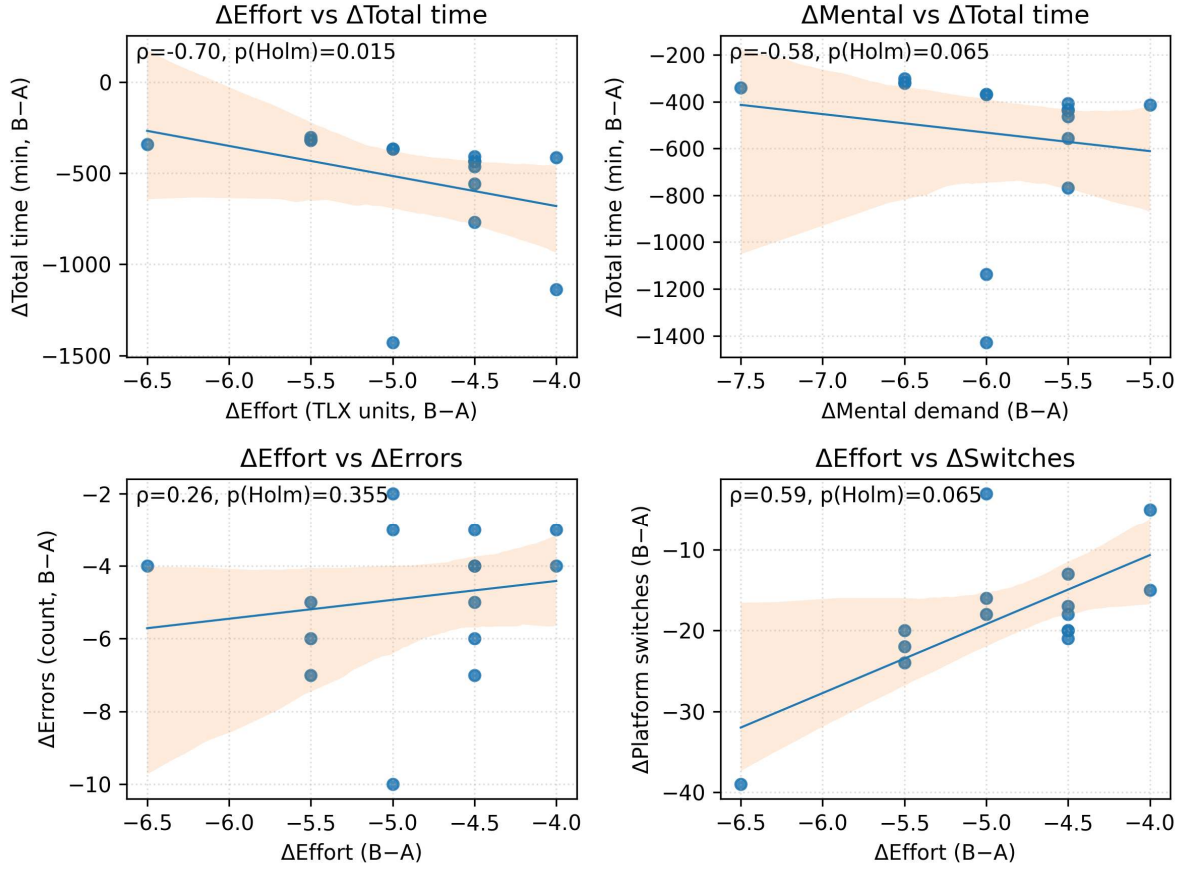


Figure 18: Correlations between subjective and objective measures within the ICTO overlay condition (Block B), visualized as  $2 \times 2$  scatterplots with regression lines and 95% confidence intervals. Each panel displays relationships (Spearman's  $\rho$ ) between: SUS vs. total time, UEQ Efficiency vs. total time, TLX Effort vs. total time, and coins recognized vs. Task 1 time.

Mental demand reduction correlated moderately with time improvements ( $\rho = -0.58$ , 95% CI  $[-0.88, 0.01]$ ,  $p = 0.065$  after Holm adjustment).

Platform switching reduction showed a trending positive correlation with effort improvements ( $\rho = 0.59$ , 95% CI  $[0.00, 0.90]$ ,  $p = 0.065$  after Holm adjustment), indicating that reductions in fragmentation correspond to decreased cognitive demands. Error reduction showed a moderate positive correlation with effort

improvement ( $\rho = 0.26$ , 95% CI  $[-0.24, 0.66]$ ,  $p = 0.355$ ), though this relationship was not statistically significant.

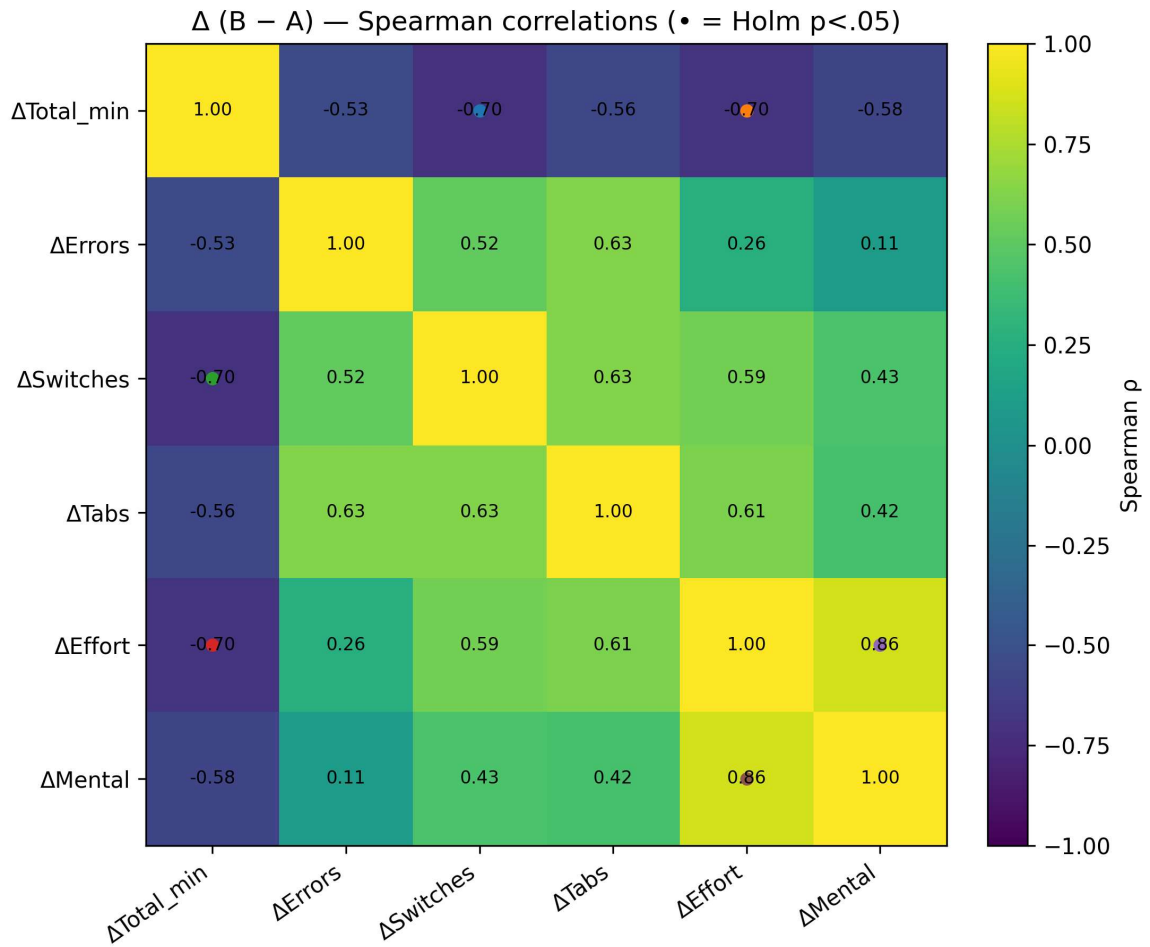


Figure 19: Complete change score correlation matrix displayed as heatmap, with Holm-significant cells marked with dots.

## 5.4 Order effects

Analysis of counterbalancing effectiveness confirmed that the experimental design successfully controlled for potential order effects. Mann-Whitney U tests comparing participants who experienced  $A \rightarrow B$  versus  $B \rightarrow A$  condition sequences revealed no significant differences across key outcome measures.

Total time improvement showed no order effect (A→B:  $M = -8.30$  minutes,  $SD = 4.78$ ; B→A:  $M = -9.54$  minutes,  $SD = 6.29$ ;  $p = 0.867$ , Hedges'  $g = 0.21$ ). Task 1 time improvement similarly showed no significant order differences (A→B:  $M = -326.7$  seconds,  $SD = 197.0$ ; B→A:  $M = -429.8$  seconds,  $SD = 296.0$ ;  $p = 0.281$ , Hedges'  $g = 0.38$ ).

Cognitive workload improvements were consistent across orders, with NASA-TLX average change scores showing no significant difference (A→B:  $M = -4.57$ ,  $SD = 0.35$ ; B→A:  $M = -4.56$ ,  $SD = 0.73$ ;  $p = 0.671$ , Hedges'  $g = -0.01$ ). Task-specific accuracy improvements also showed no order effects (coins per minute improvement: A→B:  $M = 0.067$ ,  $SD = 0.064$ ; B→A:  $M = 0.043$ ,  $SD = 0.023$ ;  $p = 0.955$ , Hedges'  $g = 0.46$ ).

The absence of significant order effects across all primary outcome measures supports the validity of the within-subjects comparison and confirms that observed improvements can be attributed to the ICTO intervention rather than learning, practice, or fatigue effects. The robust pattern of results across all measurement domains provides clear evidence for ICTO's effectiveness in reducing cognitive load and improving task efficiency, with effort reduction serving as the primary mediator between interface design and performance gains in cryptocurrency trading workflows.

## 5.5 Hypotheses Summary

Table 3 summarizes the outcomes of all hypotheses defined in §4.4, including the tested measures, statistical tests, exact p-values (Holm-adjusted where applicable), and effect sizes. ‘Supported’ indicates  $p < .05$  in the predicted direction; ‘Descriptive’ denotes overlay-only metrics without inferential testing.



Hypothesis	Measures	Test reported	Outcome
<b>H1</b>	Total time; Task 1 time; Task 2 time	Paired-samples t-test (Holm within time family)	<b>Supported</b>
H2a	Tab count	Paired-samples t-test	<b>Supported</b>
H2b	Platform switches	Paired-samples t-test	<b>Supported</b>
H2c	Error count	Paired-samples t-test	<b>Supported</b>
<b>H3</b>	CoinsRecognized_T1(Task- 1 accuracy)	Wilcoxon signed-rank (exact) (ceiling)	<b>Supported</b>
<b>H4a-f</b>	NASA-TLX (Mental, Physical, Temporal, Perf., Effort, Frustration)	Paired-samples t-tests (Holm)	<b>Supported</b>
<b>H5</b>	SUS, UEQ (overlay-only)	Descriptive (overlay- only)	<b>Descriptively supported</b>

*Table 3 Hypotheses Summary*

## 6 Discussion

### 6.1 Principal Findings

ICTO produced substantial improvements in both objective performance and subjective experience during cryptocurrency information retrieval. Across 15 experienced traders, we observed consistently large effects on time, errors, and workload, aligning with the hypothesized reduction of extraneous cognitive load.

Hypothesis outcomes: H1 (time) supported; H2a–H2c (tabs, switches, errors) supported; H3 (Task-1 accuracy) supported; H4a–H4f (NASA-TLX) supported; H5 descriptively supported;

The most striking finding was the 58% reduction in total task completion time, from  $M = 926.4$  seconds to  $M = 388.7$  seconds (Cohen's  $d^z = 1.64$ ). These exceptionally large effect sizes likely reflect the severely fragmented baseline condition characteristic of social media-driven cryptocurrency trading, where traders typically navigate across multiple platforms simultaneously. The magnitude exceeds typical HCI findings because the baseline fragmentation in this domain is more extreme than in conventional interface studies. This improvement generalized across both information gathering (Task 1:  $d^z = 1.52$ ) and analytical decision-making tasks (Task 2:  $d^z = 1.46$ ), indicating that ICTO's benefits extend beyond simple data lookup to complex cognitive workflows requiring synthesis and evaluation.

Behavioral fragmentation metrics revealed even more dramatic improvements. Tab count decreased by 87% ( $d^z = 2.53$ ), platform switches by 91% ( $d^z = 2.20$ ), and error

rates by 85% ( $d^z = 2.36$ ). These reductions directly support the theoretical prediction that information integration tools reduce extraneous cognitive load by minimizing task-switching overhead and working memory demands.

These reductions directly address the fragmented, multi-platform information environment characteristic of crypto markets documented in cryptocurrency trading environments (Chapter 2). The 91% reduction in platform switching demonstrates that ICTO successfully eliminates the information fragmentation that creates cognitive overhead in modern cryptocurrency workflows.

Subjective measures provided convergent evidence for cognitive relief. NASA-TLX scores showed reductions across all dimensions, with mental demand decreasing by nearly 6 points on the 10-point scale ( $d^z = 9.52$ ). The magnitude of these subjective improvements, combined with excellent usability ratings (SUS M = 86.3), indicates that participants experienced genuine cognitive support rather than mere efficiency gains through interface shortcuts.

## 6.2 Theoretical Implications for Cognitive Load Theory

The findings provide robust empirical support for Cognitive Load Theory, particularly regarding how information presentation shapes cognitive efficiency.

According to Sweller’s framework, intrinsic cognitive load relates to the complexity of the task itself, while extraneous load is added by suboptimal information design. The success of ICTO suggests that much of the cognitive demand in cryptocurrency trading arises from extraneous load caused by fragmented information - rather than from the inherent complexity of trading activities.

The significant correlation between reduced subjective effort and time improvement ( $\rho = -0.70$ ,  $p = 0.015$ ) offers direct evidence for cognitive offloading mechanisms.

Participants reporting the greatest decrease in perceived cognitive effort also showed the largest performance gains, indicating that ICTO effectively shifted processing demands from working memory to external technological support.

Importantly, the analysis revealed that effort reduction was the main factor mediating the relationship between interface design and performance gains. Only the correlation between effort and task completion time remained significant after correcting for multiple comparisons ( $\rho = -0.70$ ,  $p = 0.015$ ). This suggests that, in high-speed trading contexts, perceived effort is a particularly sensitive measure of interface effectiveness - perhaps more so than global assessments of cognitive load.

Overall, these results extend Cognitive Load Theory to high-stakes, time-sensitive financial decision-making in social media-intensive trading contexts. The theory's focus on minimizing split-attention effects is highly relevant for cryptocurrency trading, where information is distributed across multiple channels and timing is critical. By consolidating disparate sources into a single, integrated interface, ICTO helps eliminate split attention and supports more effective decision-making under pressure.

### 6.3 Practical Implications for Cryptocurrency Trading Interface Design

The study establishes specific design principles for reducing information fragmentation in social media-driven cryptocurrency trading environments, particularly for meme coins and emerging tokens where social signals dominate price formation. ICTO's effectiveness derived from three key architectural features that align with cognitive science principles.

First, contextual information integration eliminated the need for external navigation by embedding market data, security analytics, and price information directly within social media workflows. This approach reduced platform switching by 91%, confirming that context-aware design can dramatically minimize workflow disruption.

Second, progressive disclosure mechanisms enabled access to comprehensive analytical data without overwhelming users with excessive information density. The overlay's layered interface design supported both rapid screening and detailed analysis within a single interaction paradigm.

Third, real-time data aggregation from multiple sources (DexScreener, GeckoTerminal, RugCheck, Jupiter) provided traders with previously unprecedented access to consolidated information. This integration demonstrates that well-designed APIs and data architecture can overcome inherent market fragmentation.

These findings have immediate relevance for cryptocurrency trading platform development. The effect sizes observed suggest that similar integration approaches could yield substantial competitive advantages for trading interfaces that successfully implement cognitive load reduction principles.

## 6.4 Limitations and Methodological Considerations

Several factors limit the generalizability of these findings. The study sample consisted of 15 male participants aged 18–35, restricting applicability to other age groups.

While the within-subjects design minimized individual differences, the homogeneity of the sample means cognitive load reduction benefits may not generalize to all trader populations.

The study also focused on two highly specific workflows centered on social media scanning. These workflows do not capture the full range of activities involved in

cryptocurrency trading. Additionally, tasks were restricted to 30-minute sessions using standardized information, unlike real-world cryptocurrency trading, which often involves longer timeframes, rapidly changing markets, and a broader set of tools and strategies.

This limitation may be especially relevant for meme coin and social media-driven trading, which differs substantially from traditional cryptocurrency trading approaches. Bitcoin and major cryptocurrency trading often rely more heavily on technical analysis, macroeconomic factors, and institutional flows rather than social media sentiment. The findings may therefore have limited applicability to trading strategies focused on established cryptocurrencies where social media plays a less dominant role in price formation.

A ceiling effect in Task 1 accuracy (with all participants achieving maximum scores using ICTO) limited further analysis of speed-accuracy tradeoffs. While this shows ICTO's strength for information gathering, it prevented observing performance variation that might occur under more demanding, varied, or lengthy task conditions.

Counterbalancing analysis found no significant order effects (all  $p > 0.05$ ), demonstrating that the design effectively controlled for learning and fatigue. This increases confidence that improvements resulted from ICTO's features rather than practice or sequence effects.

The unusually large effect sizes ( $d > 2.0$ ) should be interpreted cautiously. They likely reflect the severely fragmented baseline typical of social-media-driven trading rather than universal gains from any interface change. Replication with broader tasks and more diverse samples is needed to assess stability and generalizability.

## 6.5 Future Research Directions

Several research avenues would strengthen understanding of cognitive support systems in financial trading contexts. Replication with larger, more diverse samples would enable examination of individual difference factors and provide more stable effect size estimates. Between-subjects designs could eliminate any residual concerns about within-subjects contamination, though the current order effects analysis suggests this risk is minimal.

Longitudinal studies examining sustained ICTO usage would address questions about long-term adoption, habituation effects, and integration with existing trader workflows. Extended observation periods would also enable assessment of downstream outcomes including decision quality, trading performance, and user retention.

Field studies integrating ICTO with live trading platforms would provide crucial ecological validity evidence. Such studies could examine whether laboratory-observed cognitive load reductions translate into improved financial decision-making and trading outcomes under authentic market conditions.

Comparative studies evaluating ICTO against other cryptocurrency information aggregation tools would contextualize the current findings within the broader landscape of trading technology solutions. Such research could identify which specific ICTO features contribute most substantially to cognitive load reduction.

Additionally, these findings suggest effort reduction may be a more sensitive cognitive load indicator than traditional mental demand measures in high-tempo decision-making contexts. Future research should investigate whether this effort-

primacy pattern generalizes to other information-intensive domains such as financial analysis, medical diagnosis, or emergency response coordination.

## 6.6 Conclusion

This study provides compelling evidence that thoughtfully designed information integration tools can dramatically reduce cognitive load and improve performance in complex, time-sensitive decision-making environments. This was demonstrated with a browser extension developed during this thesis: ICTO's exceptional effectiveness - demonstrated through effect sizes exceeding 2.0 across multiple outcome measures - establishes that information fragmentation represents a major, addressable barrier to efficient cryptocurrency trading.

The convergence of objective performance improvements, behavioral fragmentation reductions, and subjective cognitive relief confirms that ICTO successfully addresses core theoretical predictions from Cognitive Load Theory. By eliminating extraneous cognitive load through contextual information integration, ICTO enables traders to focus cognitive resources on analysis and decision-making rather than information gathering and navigation.

These findings have immediate implications for social media-integrated cryptocurrency trading platform development, particularly for platforms targeting meme coin and emerging token markets, though broader applications to information-intensive professional domains require further investigation across different trading contexts. The study demonstrates that browser-based overlay technologies can serve as effective cognitive support systems, providing a scalable approach to reducing information fragmentation costs across complex digital workflows.



These results also address the research gap in browser-based trading tools, which traditionally emphasize security and performance while neglecting cognitive support capabilities. ICTO demonstrates that browser extensions can serve as effective cognitive prosthetics, providing scalable solutions for information integration across professional domains.

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# Erklärung

Ich erkläre hiermit an Eides statt, dass ich die vorliegende Arbeit selbstständig und ohne unzulässige fremde Hilfe angefertigt habe. Die verwendeten Quellen sind vollständig zitiert. Darüber hinaus erkläre ich ebenfalls die Regeln für den Einsatz von künstlicher Intelligenz im Erstellprozess der vorliegenden Arbeit befolgt zu haben, zu finden im Dokument Rules for AI (siehe <https://github.com/abx-firez/HNUdocs/blob/develop/RulesForAI.pdf>).

Arbeitsschritt	KI-Werkzeuge	Beschreibung des Vorgehens
Inhaltliche Erstellung, Datenanalyse, Abbildungen	Keine	Texte/Argumentation/Statistik eigenständig; keine generative Texterstellung.
Recherche & Kurz- Zusammenfassungen	Perplexity	Überblick/Quellenvorschläge; alle Quellen im Volltext geprüft und nur bei Eignung zitiert.
Strukturierung & sprachliche Überarbeitung	ChatGPT	Gliederungsvorschläge sowie Proofreading (Stil/Grammatik); Änderungen manuell geprüft.
Programmierung (ICTO)	Gemini	Code-Hinweise/Debugging; finaler Code vom Autor erstellt und geprüft.

Ulm, den 25.08.2025,



Samuel Klefe