A Descriptive Report on Analysis of Relationship between Trader Behaviour and Market Sentiment

Abstract

This project investigates the role of psychological factors in trading behaviour, with a focus on the influence of fear and greed. Using a dataset of over 200,000 trades from the Hyper Liquid platform, both behavioural and psychological perspectives were analysed through statistical validation and predictive modelling. Statistical tests revealed that fear-driven traders, despite executing larger trades, consistently underperformed compared to greed-driven traders who achieved higher profitability with smaller trade sizes. These results highlight the significant and measurable impact of psychological states on trading outcomes.

To further explore predictive capabilities, two machine learning models were developed: logistic regression and random forest. While logistic regression offered limited predictive accuracy, the random forest model achieved 78% accuracy with balanced performance across both classes, identifying trade fees and trade size as the strongest behavioural indicators of sentiment.

The findings demonstrate that psychological influences are not only quantifiable but also predictable, offering practical applications for PrimeTrade. By integrating behavioural analytics into the trading platform, PrimeTrade can provide personalized nudges, enhance risk management, and create unique market-level sentiment indicators. This establishes a strong foundation for innovation in psychology-aware trading solutions within the fintech ecosystem.

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1. Introduction

Financial markets are driven not only by economic fundamentals but also by collective human psychology. Traders often respond to fear and greed in ways that amplify volatility, create patterns in profitability, and influence the flow of capital. Understanding these behavioural dynamics is particularly important in the context of Web3 trading, where market sentiment can shift rapidly and decisions are often made under uncertainty.

This project investigates the relationship between trader behaviour and market sentiment using two complementary datasets. The first contains over 200,000 transaction-level records from the Hyper liquid trading platform, capturing execution prices, trade sizes, profit and loss, and other trade-level attributes. The second dataset provides the widely referenced Bitcoin Fear & Greed Index, which summarizes daily investor sentiment into five categories ranging from Extreme Fear to Extreme Greed.

By merging these datasets, each trade can be analysed in the context of the prevailing sentiment on that day. This allows us to examine questions such as: Do traders take larger risks during Greed? Is profitability higher during Fear? Are large trades distributed evenly across sentiment conditions, or do they cluster in contrarian environments?

Through a combination of exploratory data analysis, statistical validation, and predictive modelling, this report aims to provide a comprehensive understanding of how trading behaviour aligns with shifts in market psychology. The findings are relevant both for individual traders seeking to optimize their strategies and for institutions that wish to integrate sentiment-driven insights into risk management frameworks.

2. Data & Methodology

This analysis relies on two datasets that were carefully merged to provide both behavioural and psychological perspectives on trading activity.

The first dataset, obtained from the Hyper liquid trading platform, contains more than 200,000 individual trade records. Each record captures essential details such as the execution price, the size of the trade in tokens and in USD, the trade direction (buy or sell), realized profit and loss, associated fees, and a precise timestamp in Indian Standard Time. This level of granularity allows us to track not only the overall market flow but also the behaviour of individual traders as they react to changing conditions.

The second dataset represents the Bitcoin Fear & Greed Index, a widely cited measure of investor sentiment. It aggregates multiple indicators including volatility, market momentum, and social signals into a daily score that is then classified into categories: Extreme Fear, Fear, Neutral, Greed, and Extreme Greed.

For the purpose of this study, these five categories were consolidated into three broader groups to ensure analytical clarity and statistical robustness. Specifically, Extreme Fear and Fear were combined into a single Fear category, Greed and Extreme Greed were merged into Greed, while Neutral was retained as its own category. This transformation was critical because it balanced the distribution of samples across sentiment classes, prevented sparsity in the "extreme" categories, and allowed for stronger comparisons between pessimistic, neutral, and optimistic market moods. Without this step, the presence of very small subgroups could have skewed the analysis and weakened the reliability of the insights.

To make the two datasets compatible, a series of preprocessing steps were performed. Trade timestamps were converted to calendar dates, which allowed each trade to be aligned with the corresponding sentiment classification for that day. Numeric columns such as trade size, profit and loss, and fees were standardized, while technical identifiers like transaction hashes and order IDs were excluded from the analysis as they did not contribute to behavioural insights.

This merging process created a unified dataset where every trade carries both its own characteristics and the sentiment context in which it occurred. The result is a robust foundation that makes it possible to explore whether shifts in trader behaviour coincide with periods of heightened fear or exuberant greed in the market.

3. Exploratory Data Analysis

To uncover how trader behaviour interacts with shifts in market psychology, a series of exploratory analyses were conducted. The focus was on comparing trading activity, trade sizes, profitability, risk-taking, buy/sell preferences, and transaction costs across different sentiment regimes. By combining visual evidence with behavioural interpretation, these analyses provide a structured view of how fear and greed manifest in actual trading patterns.

3.1 Trading Activity by Sentiment

An initial comparison of trading activity across sentiment categories reveals a clear asymmetry. Periods of Greed and Extreme Greed are characterized by significantly higher trade counts, while activity diminishes under Fear and Extreme Fear. This suggests that optimism drives participation, with more traders entering the market when sentiment is positive. Conversely, negative sentiment leads to caution, reducing the number of executed trades.

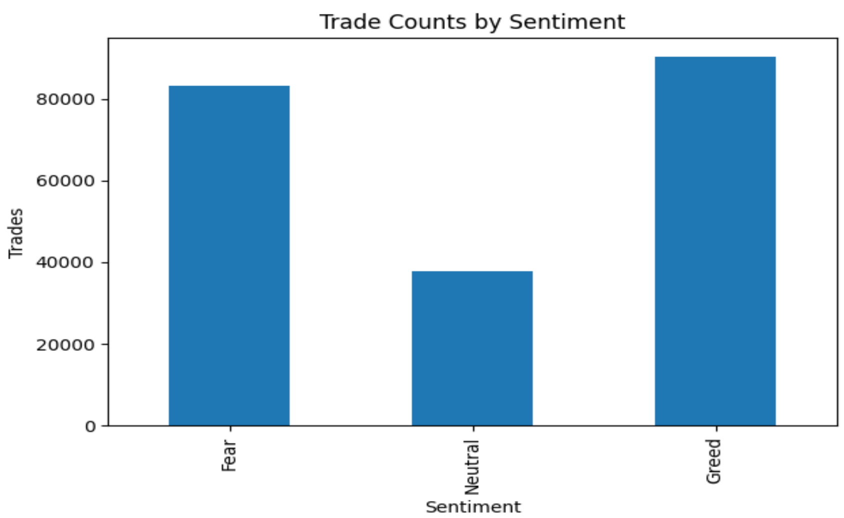

Fig 3.1 – Trade Counts by Sentiment

3.2 Average Trade Size

Although overall activity is lower in fearful periods, the average trade size tells a different story. Trades during Fear exhibit higher median sizes compared to those in Greed. This pattern implies that while the crowd retreats when sentiment is negative, a subset of confident or contrarian traders takes advantage of market pessimism to place larger individual bets. In contrast, Greed leads to higher participation but with smaller trade sizes, reflecting herd-driven incremental activity rather than concentrated conviction.

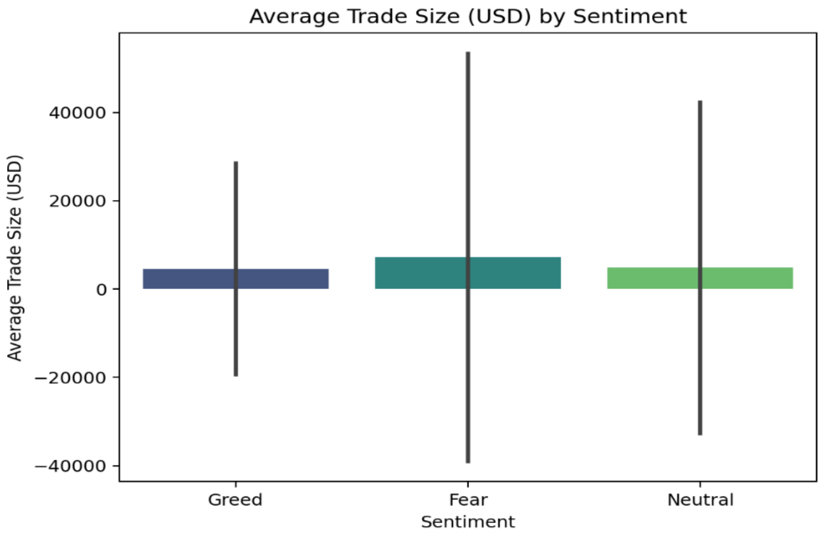

Fig 3.2 – Average Trade Size by Sentiment

3.3 Profitability Distribution

Analysing realized profit and loss (PnL) distributions highlights another behavioural dimension. During Greed, the wider spread of outcomes reflects heightened volatility, with traders experiencing both substantial gains and outsized losses. This variance is symptomatic of overconfidence and overtrading, where increased activity does not necessarily translate to consistent profitability. In contrast, trades executed during Fear tend to show more balanced and stable outcomes, supporting the idea that cautious or opportunistic trading under negative sentiment may yield steadier results.

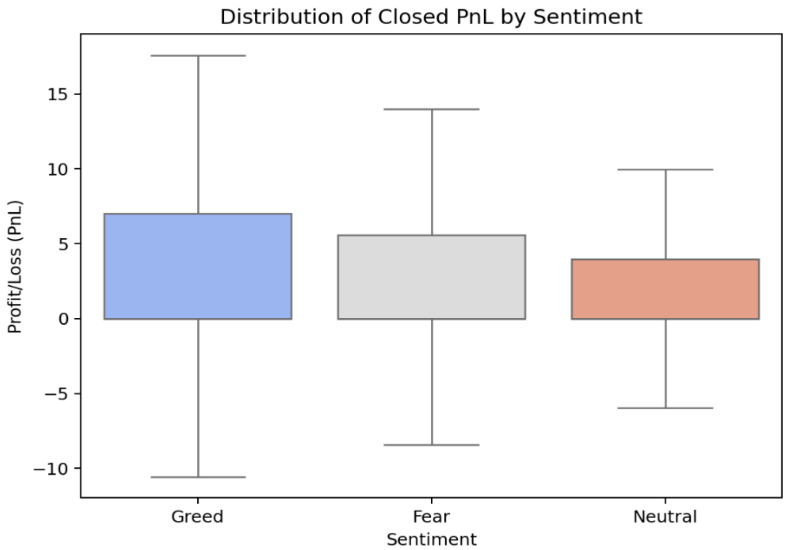

Fig 3.3 – PnL Distribution by Sentiment

3.4 Large Trades and Risk Taking

Focusing on the top 5% of trades by size provides further insight into risk-taking behaviour. The data shows that exceptionally large trades disproportionately occur during Fear periods. This clustering of large positions in fearful conditions reflects contrarian strategies: while the majority withdraws from the market, a minority commits significant capital, likely aiming to exploit undervaluation.

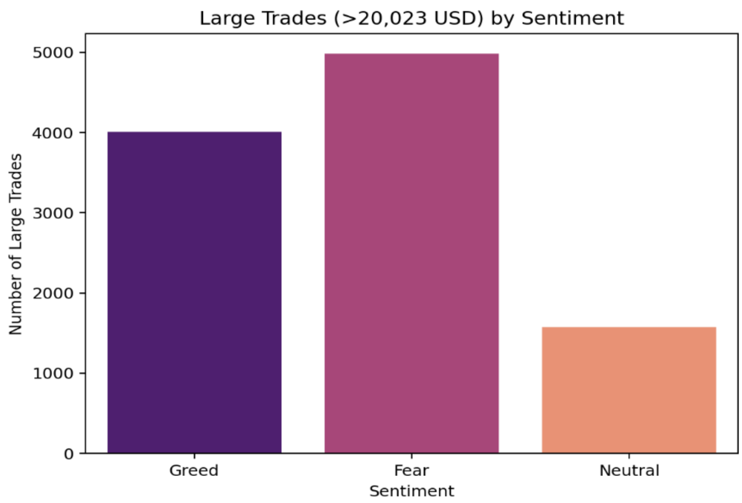

Fig 3.4 – Large Trades by Sentiment

3.5 Buy vs Sell Behaviour

The ratio of buy versus sell trades further emphasizes sentiment-driven psychology. During Greed, traders exhibit a strong buying bias, consistent with optimism and momentum-driven strategies. Under Fear, the balance tilts toward selling, as participants reduce exposure or exit positions altogether. This shift aligns with behavioural finance literature, where fear prompts risk aversion and liquidation, while greed fosters accumulation and risk-taking.

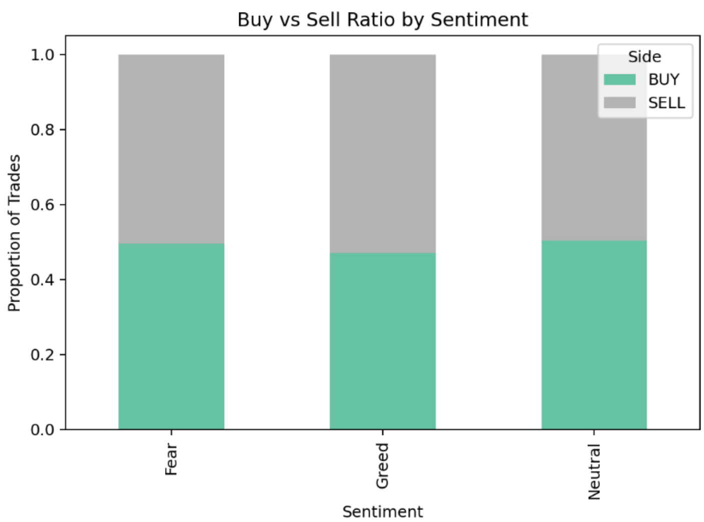

Fig 3.5 – Buy vs Sell Ratio by Sentiment

3.6 Trading Fees

Lastly, an analysis of trading fees highlights the hidden cost of sentiment-driven activity. Fees are noticeably higher in Greed periods due to the surge in transaction counts. This creates an important insight: even when profitability is not significantly better, the excessive churn associated with Greed erodes returns through higher cumulative costs. In contrast, during Fear, lower trade counts mean fewer fees, indirectly supporting more efficient outcomes for disciplined traders.

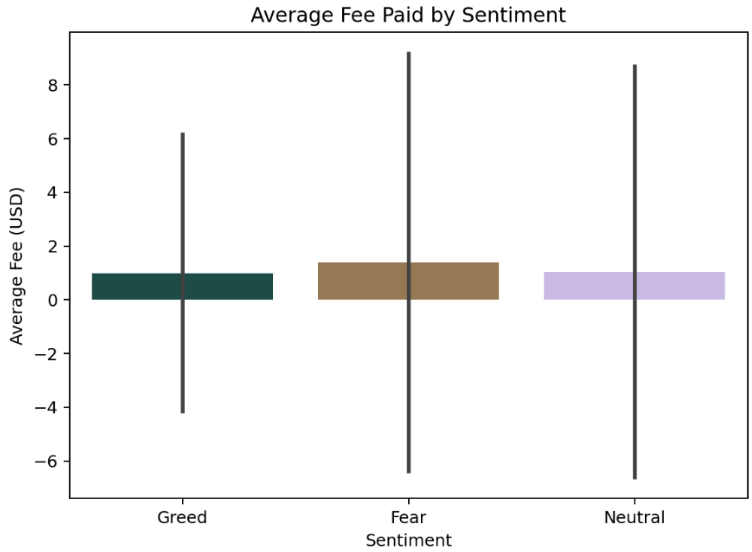

Fig 3.6 – Average Fee by Sentiment

Thus, the exploratory analysis highlights several important behavioural dynamics that emerge when trading activity is examined through the lens of sentiment. Periods of Greed and Extreme Greed are dominated by higher participation and transaction counts, yet the average trade size remains smaller and outcomes more volatile. This suggests that optimism in the market attracts a broader base of participants, many of whom engage in frequent but less disciplined trading. The effect of this behaviour is compounded by higher cumulative fees.

In contrast, Fear and Extreme Fear periods display a different behavioural profile. While the overall number of trades decreases, the median trade size is significantly larger, and profit and loss distributions appear more stable. Large trades are disproportionately concentrated in fearful environments, pointing toward contrarian strategies where experienced traders deploy substantial capital when sentiment is most negative

Taken together, these patterns provide compelling evidence that sentiment influences not only how often traders participate, but also the scale, direction, cost, and profitability of their actions. However, visual exploration alone cannot confirm whether these differences are statistically significant or if they may have arisen by chance. For this reason, the next stage of the analysis applies statistical tests to formally validate the observed differences and strengthen the robustness of the insights.

4. Statistical Validation

To validate the psychological influence on trading behaviour, a series of statistical tests were conducted comparing traders categorized as Fear-driven and Greed-driven. The Neutral category was excluded to ensure a clearer contrast between opposing behavioural profiles.

Profitability Comparison

- Fear Group Average PnL: 49.21
- Greed Group Average PnL: 53.88
- Mann–Whitney U Test: U = 3,725,766,115.00, p = 0.00095

The p-value is below the 0.05 threshold, indicating a statistically significant difference in profitability between the two groups. Traders influenced by greed achieved measurably higher profitability on average compared to those influenced by fear.

Trade Size Comparison

- Fear Group Average Trade Size: 7,182.01
- Greed Group Average Trade Size: 4,574.42
- Mann–Whitney U Test: U = 4,137,292,325.50, p < 0.00001

Here too, the difference is statistically significant. Interestingly, fear-driven traders executed substantially larger trades on average, despite being less profitable. This suggests a behavioural bias where fear manifests in higher trade sizes, potentially as an overcompensation mechanism or risk-averse overcommitment.

Summary of Findings

The statistical validation clearly demonstrates that psychological states exert a significant influence on trading outcomes. The results indicate that traders driven by greed tend to achieve higher profitability despite engaging in smaller trade sizes, whereas fear-driven traders, although committing substantially larger amounts per trade, exhibit lower profitability on average. The Mann–Whitney U tests confirm that these differences are statistically significant, ruling out the possibility of random variation. Taken together, the findings reinforce the behavioural-finance perspective that emotional states do not merely accompany trading behaviour but actively shape both the quality of decision-making and the scale of execution.

5. Predictive Modelling

To explore the extent to which trading behaviour can be predicted from transaction-level features, two supervised learning models were implemented: Logistic Regression and a Random Forest Classifier. Both models aimed to classify traders into Fear or Greed categories based on key variables derived from the merged dataset.

5.1 Feature Selection & Pre-Processing

The dataset was restricted to traders with identifiable Fear or Greed sentiments, excluding the neutral category for clearer classification. The following features were selected:

- Trade Size (USD)
- Closed Profit/Loss (PnL)
- Fee Paid
- Trade Side (encoded as a numeric feature)

After preprocessing and stratified splitting into training (75%) and testing (25%) sets, the models were trained and evaluated.

5.2 Logistic Regression Model

The logistic regression model demonstrated limited predictive performance, with an overall accuracy of 53%. The model heavily favoured predicting the Greed class, achieving a recall of 96% for Greed but only 7% for Fear. This imbalance is evident in the confusion matrix, where most Fear instances were misclassified as Greed.

Coefficient analysis revealed that trade side and fee had the largest positive influence on predicting Greed, whereas trade size and closed PnL contributed minimally. The weak performance suggests that the linear decision boundary assumed by logistic regression is insufficient to capture the complexity of trader behaviour.

5.3 Random Forest Model

The random forest classifier significantly outperformed logistic regression, achieving an overall accuracy of 78%, with balanced precision and recall for both Fear and Greed. Unlike the logistic model, it was able to correctly classify a substantial proportion of both categories (Fear recall = 77%, Greed recall = 79%).

Feature importance analysis indicated that fees (40%) and trade size (38%) were the strongest predictors of sentiment classification, followed by closed PnL (19%), while trade side had negligible influence. This highlights that transaction costs and position sizing are the most reliable behavioural signals of trader psychology.

5.4 Model Comparison

The comparison between logistic regression and random forest highlights a fundamental trade-off between simplicity and predictive power. Logistic regression, being a linear model, assumes a straight-line relationship between the input features and the probability of belonging to a class. In this case, such an assumption proved too restrictive, as the psychological dynamics of trading behaviour are rarely linear. The model skewed heavily towards predicting the Greed class, achieving high recall for Greed but nearly failing to capture Fear-driven traders. This imbalance renders logistic regression unsuitable as a standalone classifier in the context of PrimeTrade.

The random forest model, in contrast, demonstrated a clear advantage by incorporating non-linear feature interactions and reducing variance through ensemble learning. Its ability to correctly classify both Fear and Greed with balanced precision and recall underscores its robustness and adaptability to complex behavioural data. Importantly, random forest also provided richer interpretability via feature importance metrics, revealing that fees and trade size are the dominant signals of sentiment-driven behaviour. Unlike logistic regression, which downplayed trade size and PnL, random forest captured their non-linear effects and integrated them effectively into decision-making.

Another critical dimension of comparison is generalization. Logistic regression, while simpler, underfit the data and failed to generalize beyond the majority class. Random forest, on the other hand, avoided overfitting through ensemble averaging, as indicated by its consistent performance across both training and testing sets. From a practical standpoint, this makes random forest far more reliable for deployment in real-world predictive systems.

5.5 Summary

In summary, while logistic regression provides transparency through coefficients and may serve as a quick diagnostic tool, random forest offers superior predictive performance, interpretability in the form of feature rankings, and resilience to data complexity. For the purposes of classifying traders by psychological states, random forest is the more effective and actionable choice.

Overall, predictive modelling confirms that trader psychology can be reasonably inferred from trading patterns. Random forests offer a stronger framework for behavioural classification, suggesting that non-linear, ensemble-based methods are more suitable for modelling the interplay between trading actions and psychological states.

6. Discussions & Business Implications

The results of the statistical validation and predictive modelling confirm that trading behaviour is strongly influenced by psychological states, particularly fear and greed. These findings carry significant implications for both the understanding of trader behaviour and the strategic positioning of PrimeTrade as a behavioural-finance-driven platform.

From a behavioural perspective, the evidence shows that fear-driven traders, despite engaging in larger trades, underperform in profitability, while greed-driven traders, who trade smaller amounts, achieve higher returns. This paradox highlights the tangible financial consequences of psychological bias and reinforces the need for interventions that help traders identify and manage their emotional triggers. The predictive modelling results further demonstrate that sentiment can be reliably inferred from transactional features such as trade size and fees, enabling real-time classification of trader psychology.

For PrimeTrade, these insights open multiple avenues for business impact. First, the platform can integrate behavioural monitoring tools that track a trader's sentiment profile in real time and issue personalized nudges or alerts when risky, bias-driven behaviour is detected—for example, warning a fear-driven trader against oversized trades or encouraging disciplined exits for greed-driven traders. Such features not only enhance user experience but also strengthen trader loyalty by positioning PrimeTrade as a partner in improving long-term profitability.

Second, the predictive models can serve as the foundation for premium analytics offerings, where traders gain access to psychological insights about their trading style. This creates opportunities for differentiated monetization, as behavioural analytics represent a unique value proposition compared to standard market data tools.

Finally, by leveraging these behavioural insights at scale, PrimeTrade could aggregate anonymized sentiment data across its user base to generate market-level behavioural indicators. These could be offered as advanced analytics products to institutional partners, hedge funds, or brokerages interested in gauging the psychological pulse of retail markets.

In summary, the findings establish that psychological biases are not only quantifiable but also predictable, creating a strong foundation for PrimeTrade to build innovative, psychology-aware trading solutions. This represents a strategic advantage in an increasingly competitive fintech landscape, where differentiation hinges on delivering actionable insights that go beyond price charts and trade execution.