📊 TRADER BEHAVIOR INSIGHTS BASED ON MARKET SENTIMENT

ANALYZING HOW EMOTIONS LIKE FEAR & GREED IMPACT TRADING DECISIONS

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PROJECT OVERVIEW

- This project explores how crypto traders behave under different market sentiments.

- It combines two datasets:
  - ➤ Fear 😟 & Greed 😄 Index (emotions in the market)
  - ➤ Historical Trading Data (actual trades made by users)

- The goal is to understand if emotions like fear or greed affect trader decisions and profit outcomes.

- This analysis helps uncover useful patterns that could guide better trading strategies.📉

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🎯 PROJECT GOALS & OBJECTIVES

🧩 WHAT THIS PROJECT AIMS TO DO:

- 📊 Analyze trader performance under different market sentiments.
  Understand how profit/loss varies with Fear, Greed, etc.
- 🧠 Study behavioral trends.
  Do traders take more risks during Greed? Do they panic in Fear?
- 📈 Explore trade characteristics
  Compare size, direction (Buy/Sell), and frequency under each sentiment
- 🔍 Uncover hidden patterns
  Look for subtle shifts in strategy or volume based on market emotions
- 💡 Generate practical insights
  Help traders or platforms make smarter, emotion-aware decisions

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DATASETS USED

Fear & Greed Index
(fear_greed_index.csv)

- Date: The day the sentiment was recorded
- Classification: Emotion label like Fear, Greed, etc.
- Value: Numeric score (0–100) showing sentiment strength
- Timestamp: Full date-time (used only to extract date)

Historical Trader Data
(historical_data.csv)

- Account: Trader ID
- Execution Price / Size: Price + amount of each trade
- Side: BUY or SELL
- Closed PnL: Profit or loss made from the trade
- Timestamp: Trade execution time

The Datasets can be Accessed at : fear_greed_index.csv , historical_data.csv

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TOOLS AND TECHNOLOGIES USED

TOOL	PURPOSE
Python	Main programming language for analysis
Pandas	Data cleaning, manipulation, and merging
Matplotlib	Basic charting and visual exploration
Seaborn	Beautiful visualizations (barplots, etc.)
Jupyter Notebook	Writing, testing, and documenting code
Canva	Designing the final visual report

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DATA CLEANING & PREPARATION

LOAD RAW DATASETS

```
fear_greed_df = pd.read_csv("fear_greed_index.csv")
historical_df = pd.read_csv("historical_data.csv")
```

🧾 Used pandas to load both CSV files into dataframes.

CONVERT TIMESTAMP → DATE

🧾 Formatted timestamp to datetime and extracted only the date.

```
historical_df.drop(columns=["transaction_hash", "Order ID", "Trade ID", "Timestamp"], inplace=True)

fear_greed_df.drop(columns=["timestamp","value"], inplace=True)
```

```
historical_df["date"] = pd.to_datetime(historical_df["timestamp"], format="%d-%m-%Y %H:%M")
fear_greed_df["date"] = pd.to_datetime(fear_greed_df["timestamp"]).dt.date
```

DROP UNNECESSARY COLUMNS

🧾 Removed timestamp and unused fields for cleaner structure.

Account	Coin	execution_price	size_tokens	size_usd	Side	start_position	Direction	closed_pnl	Crossed	Fee	date
0xae5eacaf9c6b9111fd53034a602c192a04e082ed	@107	7.9769	986.87	7872.16	BUY	0.000000	Buy	0.0	True	0.345404	2024-12-02
0xae5eacaf9c6b9111fd53034a602c192a04e082ed	@107	7.9800	16.00	127.68	BUY	986.524596	Buy	0.0	True	0.005600	2024-12-02
0xae5eacaf9c6b9111fd53034a602c192a04e082ed	@107	7.9855	144.09	1150.63	BUY	1002.518996	Buy	0.0	True	0.050431	2024-12-02
0xae5eacaf9c6b9111fd53034a602c192a04e082ed	@107	7.9874	142.98	1142.04	BUY	1146.558564	Buy	0.0	True	0.050043	2024-12-02
0xae5eacaf9c6b9111fd53034a602c192a04e082ed	@107	7.9894	8.73	69.75	BUY	1289.488521	Buy	0.0	True	0.003055	2024-12-02

classification	date
Fear	2018-02-01
Extreme Fear	2018-02-02
Fear	2018-02-03
Extreme Fear	2018-02-04
Extreme Fear	2018-02-05

✅ Cleaned both datasets by:

Converting timestamps to readable date format | Removing unused columns | Ensuring both datasets have a common date column

This prepared our data for merging and analysis!

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MERGING DATASETS & FINAL OUTPUT

MERGE ON 'DATE' COLUMN

🧾 Merged both datasets on the date column using left join.

```
merged_df = pd.merge(historical_cleaned_df,fear_greed_df,how='left',on='date')
merged_df.head()
```

✅ Merged sentiment data with trade records using 'date'
Final dataset now contains:
- Daily sentiment (classification)
- Trader side (BUY/SELL)
- Profit/Loss
- Trade size and more

This unified view lets us analyze how emotions impact real trades.

date	closed_pnl	Side	size_usd	classification
2024-12-02	0.0	BUY	7872.16	Extreme Greed
2024-12-02	0.0	BUY	127.68	Extreme Greed
2024-12-02	0.0	BUY	1150.63	Extreme Greed
2024-12-02	0.0	BUY	1142.04	Extreme Greed
2024-12-02	0.0	BUY	69.75	Extreme Greed

Final Merged Dataset Preview

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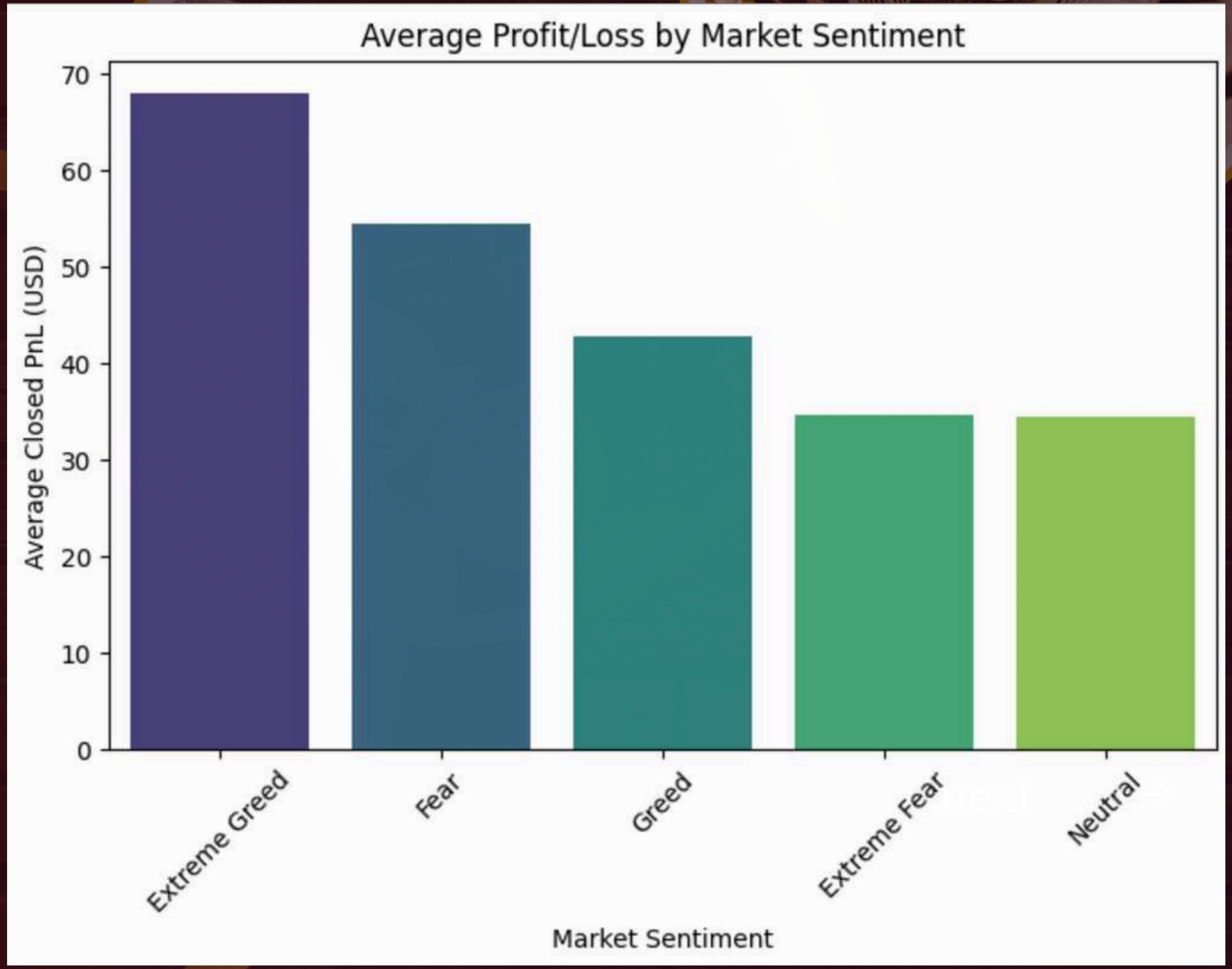
TRADER BEHAVIOR BY MARKET SENTIMENT

1. AVERAGE PROFIT/LOSS BY MARKET SENTIMENT

Calculated the average closed_pnl (profit/loss) for trades under each sentiment category (e.g., Fear, Greed, etc.)

```
avg_pnl = merged_df.groupby("classification")["closed_pnl"].mean().sort_values(ascending=False).reset_index()
avg_pnl
```

- Traders made the most profit during **Extreme Greed,** likely riding strong bullish trends.
- Even during **Fear**, average profits were good — possibly due to smarter, cautious trading.
- Lowest profits were seen during **Extreme Fear** and **Neutral**, suggesting hesitation or panic-driven decisions.

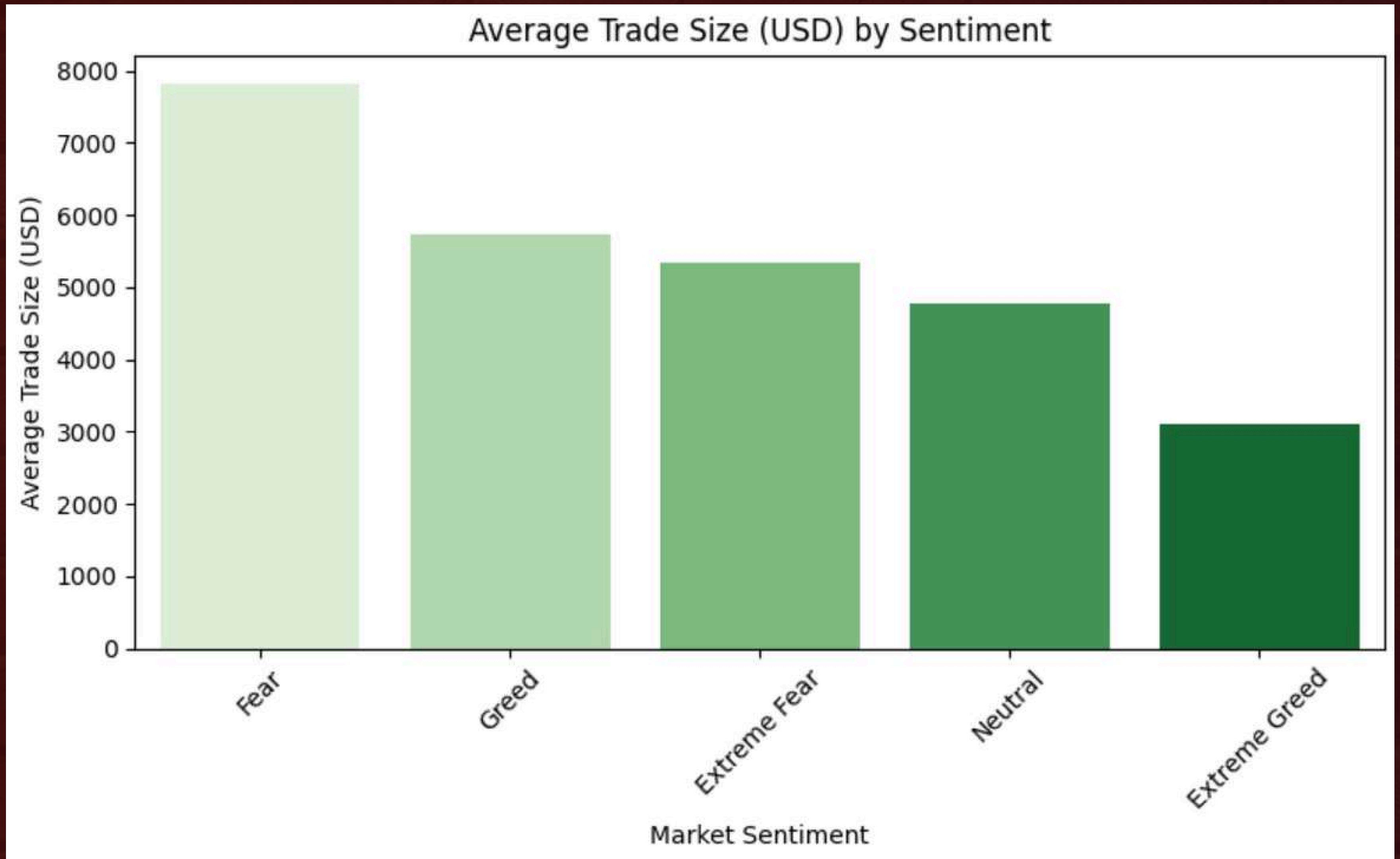


TRADER BEHAVIOR BY MARKET SENTIMENT

2. AVERAGE TRADE SIZE BY MARKET SENTIMENT

Calculated the average size_usd (trade value in USD) for each sentiment classification to understand risk-taking behavior.

```
avg_pnl = merged_df.groupby("classification")["closed_pnl"].mean().sort_values(ascending=False).reset_index()
avg_pnl
```



- During **Fear**, traders placed the largest trades, possibly trying to capitalize on volatile markets.
- Surprisingly, trade sizes were lowest during Extreme Greed — suggesting smaller, quick-profit trades.
- Emotions clearly influence not just profit but how much risk traders take.

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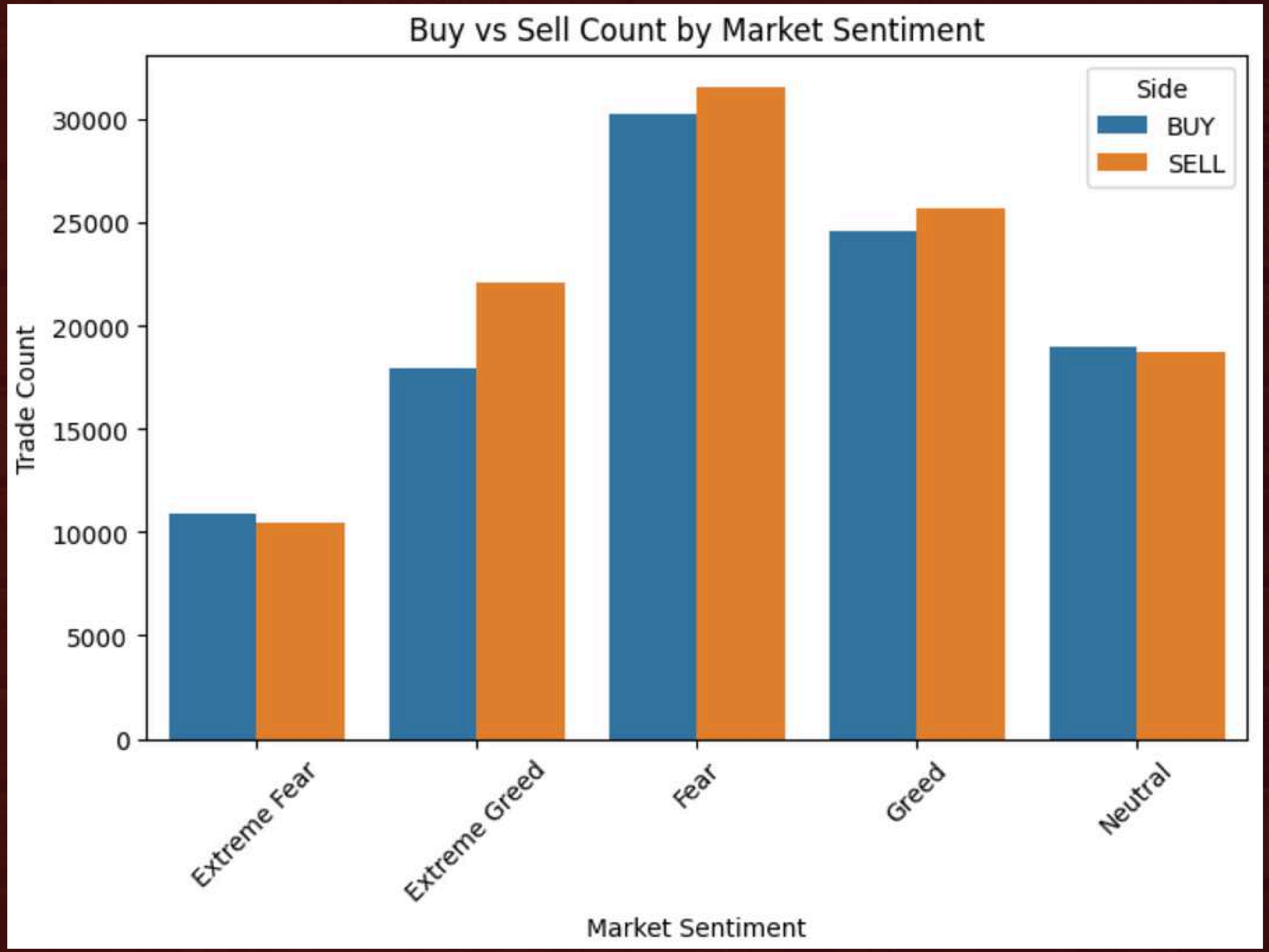
TRADER BEHAVIOR BY MARKET SENTIMENT

3. BUY VS SELL BEHAVIOUR BY MARKET SENTIMENT

Analyzed how many BUY vs SELL trades occurred under each sentiment label to understand trader bias.

```
buy_sell_counts = merged_df.groupby("classification")["Side"].value_counts().unstack().reset_index()
buy_sell_counts
```



- In Greed and Extreme Greed, BUY trades were higher — traders showed bullish confidence.
- During Fear, SELL trades increased — suggesting risk-avoidance or panic exits.
- Market emotions clearly affect trading direction, not just size or profit.

HIDDEN PATTERNS & KEY INSIGHTS

What We Discovered:

- Traders made the highest profits during Extreme Greed, suggesting they capitalized on strong bullish trends.
- Surprisingly, trade sizes were largest during Fear, showing that some traders took bigger risks in uncertain conditions.
- Buy/Sell direction clearly shifted with sentiment:
- More BUYs during Greed and Extreme Greed
- More SELLs during Fear and Extreme Fear

Why It Matters:

- These patterns highlight how market emotions directly influence trading behavior — not just in outcomes, but in size, direction, and timing.
- Platforms can use these insights to build smarter alerts, risk models, or training tools for their users.
- Traders themselves can adjust strategies based on emotional market phases to improve results.

SMART STRATEGY RECOMMENDATIONS

~ SENTIMENT AWARE TRADING STRATEGY

Use real-time Fear & Greed Index to adjust trading behavior:

- Scale back risk during Extreme Fear to avoid panic-driven losses
- Avoid overconfidence in Extreme Greed by locking in profits earlier

~ EMOTION TRIGGERED TRADE ALERTS

Platforms can trigger helpful alerts when sentiment hits extreme levels:

- During Fear, suggest caution and risk control
- During Greed, warn against impulsive overtrading

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THANK YOU!

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