



Behavioral Trading Analysis System

DONE BY -

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Problem & Use Cases

Problem Statement

1. Retail investors often make emotion-driven decisions, leading to suboptimal outcomes.
2. There is no structured way to analyze their behaviour, detect cognitive biases, and quantify their impact on portfolios and risk.



Key Use Cases

Behavioral Self-Audit

Objectively understand actual trading behavior across market regimes.

Post-Event Analysis

Identify revenge trading or overconfidence after wins/losses with concrete evidence.

Discipline Detection

Pinpoint when and why technical signals are ignored.

Personalized Feedback

Flag trades deviating from individual norms, not generic rules.

Problem Background

'\$12 billion gone every year.': Why Saurabh Mukherjea says F&O trading is hurting Indian middle-class investors

SEBI data indicates retail investors lose \$12 billion annually in F&O trading, primarily affecting 30-40-year-old males from small towns. Mukherjea emphasizes the need for policy changes to protect these investors from structural imbalances favoring institutional traders.

On July 3, 2025, India's market regulator Sebi barred the American firm [Jane Street](#) from trading in the Indian stock market, accusing it of profiting from pump-and-dump operations involving shares and their derivatives. The order said that Jane Street made a profit of Rs 36,502 crore from January 2023 to March 2025. Of course, not all of this was because of the pumping and dumping that Jane Street stands accused of.

On July 7, 2025, Sebi published [a study](#), in which it said that in 2024-25, 91 out of 100 individual traders trading in derivatives of shares, lost money. Earlier Sebi had published similar data for 2023-24 as well. So, this is not a one-off and implies that almost all retail investors lose money when they try trading in derivatives of shares.

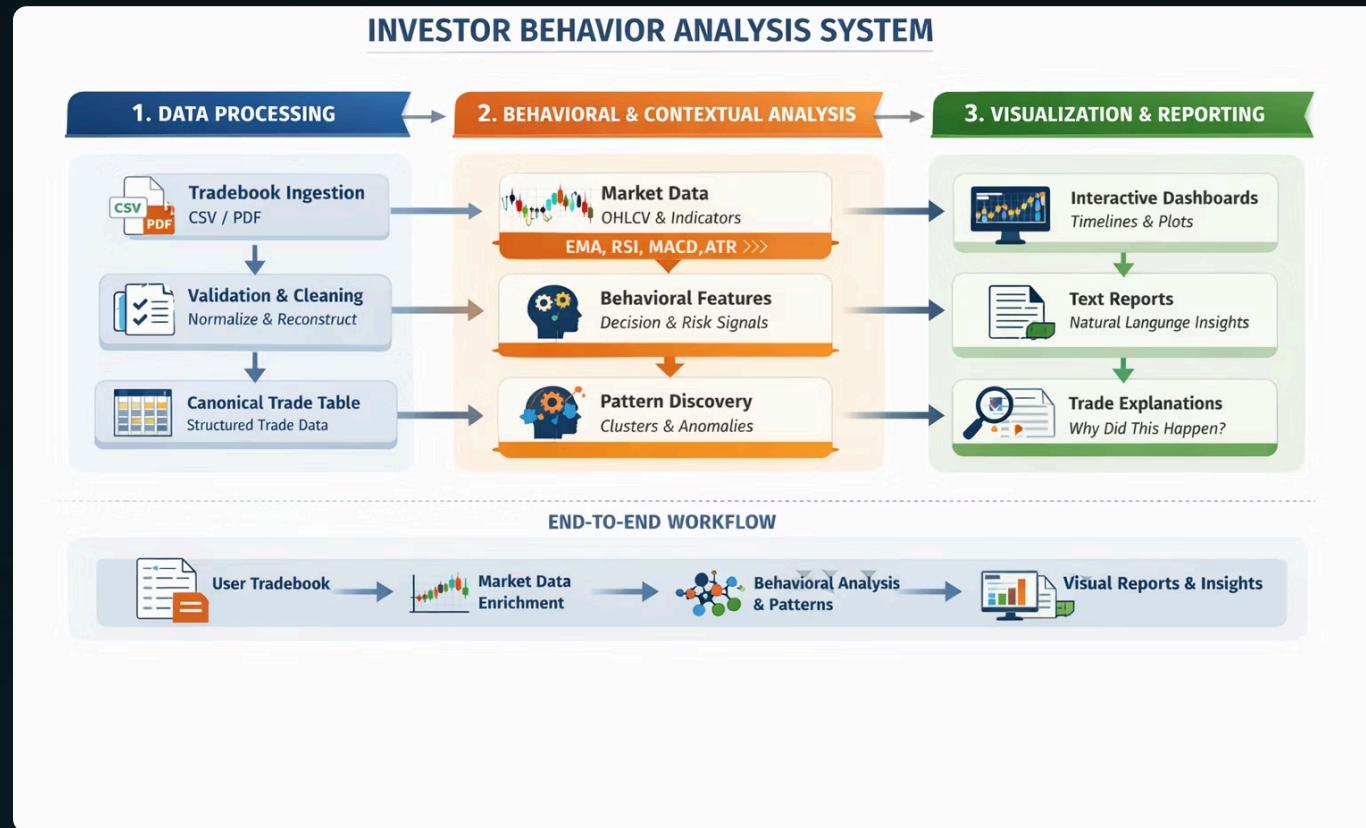
In 2025, SEBI published its report, which indicated that about 90% of individual investors lose money, which highlights how difficult it can be to succeed in the stock market.

But why do retail traders consistently lose money while institutional investors consistently profit?

Problem Research & Findings

- SEBI's 2025 report indicates individual investors lose money in the stock market (ssrn-5255947) primarily due to psychological pitfalls like FOMO and revenge trading, information asymmetry against institutional investors, poor risk management, and excessive trading costs that erode small profits.
- A study finds that psychological and behavioural factors systematically influence market behaviour, showing that investor decisions deviate from rational models and are shaped by cognitive biases and emotional responses. (Preprints202502.2000.v1)
- Higher financial literacy improves investment decisions, but behavioural biases like overconfidence, herding, and loss aversion still significantly distort investor choices even among informed investors([https://www.researchgate.net/publication/354078097 Impact of Financial Literacy and Behavioral Biases on Investment Decision-making](https://www.researchgate.net/publication/354078097_Impact_of_Financial_Literacy_and_Behavioral_Biases_on_Investment_Decision-making))

Proposed Solution



End-to-End Project Description

The system focuses on behavioral analysis, not price prediction or strategy optimization. It helps Retail investors understand their actions under various market conditions.

01

Stage 1: Data Ingestion & Normalization

Loads and validates trade data from CSVs or PDFs, cleaning and normalizing it into a canonical trade-event table. This includes reconstructing positions and calculating derived metrics like holding duration and P&L.



02

Stage 2: Behavioral & Contextual Analysis

Enriches trade data with market context (OHLCV) and engineers behavioral features (risk, sequence, regime sensitivity). It then constructs personalized baselines and discovers patterns through clustering, change point, and anomaly detection.



End-to-End Project Description

The final stage focuses on making complex behavioral insights accessible and actionable through interactive visualizations and natural language explanations.

Stage 3: Visualization (Total - 15)

Visualization	Purpose
Behavioral Regime Timeline	Shows how behavioral clusters evolve over time, overlaid with market regimes and detected change points.
Trade Journey Timeline	Visualizes each trade from entry to exit, including holding duration and realized P&L.
Post-Loss Behavior Analysis Chart	Highlights behavioral shifts after losses to detect revenge trading patterns.
MACD Stock Charts with Trade Overlay	Assesses timing and momentum alignment using MACD with trade markers.
Trade Frequency & Activity Heatmap	Visualizes trading intensity over time to identify overtrading or inactivity.

Explainable AI (XAI)

Rule-Based NLG

Generates deterministic, trustworthy explanations like "This trade deviated due to position sizing."

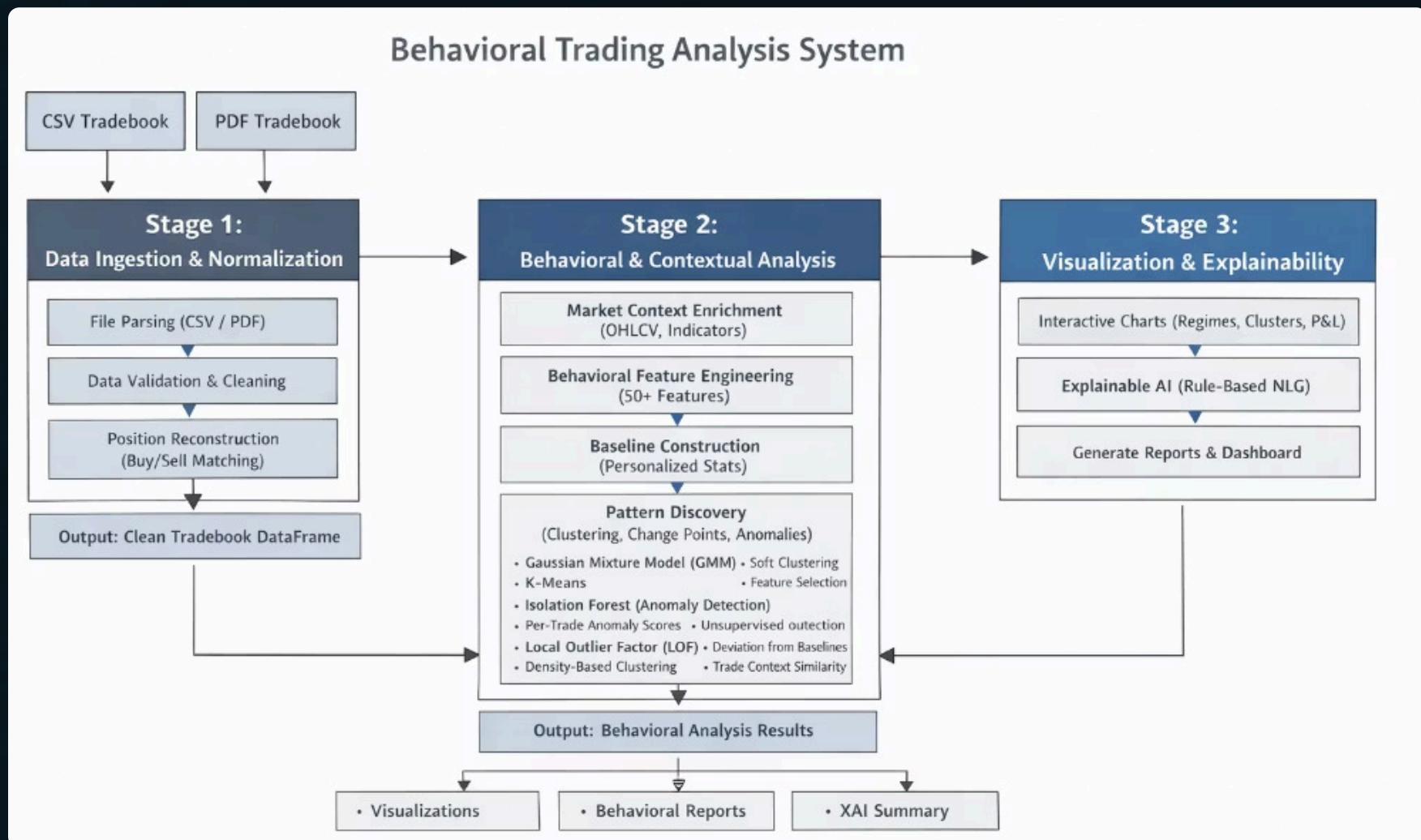
Feature Attribution

Ranks feature contributions for clustering/anomaly outputs, explaining why a trade belongs to a certain cluster.

Counterfactual Explanations

Provides intuitive insights, e.g., "If position size were normal, this trade would align with baseline."

System Design and Workflow



Results

Implementation GitHub Link - <https://github.com/Sanjivanhari18/Behavioural-Bias-in-Trading-ML>



References

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