Neuromarketing Predictors Of Retail Trading Surges: A Brain-Behavior Analysis Using Indian Stock App Users

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Abstract

India's rapid transition from conventional investing to app-mediated securities trading has created an environment in which investor attention, emotional arousal, behavioral bias, interface design and market information interact almost instantaneously. This study develops and tests a neuromarketing-based framework for explaining short-duration retail trading surges among Indian stock-app users. The proposed model integrates electroencephalographic measures of approach-related neural activity and cognitive engagement, eye-tracking indicators of visual attention, electrodermal arousal, self-reported behavioral biases and observed trading responses. The conceptual foundation combines consumer neuroscience, the Stimulus-Organism-Response framework, behavioral finance and investor-attention theory. Recent evidence demonstrates that EEG and multimodal physiological measures can predict consumer preferences and purchase decisions with meaningful out-of-sample accuracy, while experimental financial research shows that gamification, attention cues and digital nudges can increase trading volume and financial risk-taking. Recent Indian evidence further documents the importance of loss aversion, herding, anchoring, overconfidence, social-media exposure and financial literacy in retail investment decisions.

The proposed empirical design involves active Indian stock-app users exposed to controlled trading-interface conditions varying market momentum, social proof, urgency cues and gamification intensity. Brain-behavior indicators are linked to trading initiation, order frequency, response latency, position size and speculative-risk preference. The analytical architecture combines confirmatory factor analysis, reliability and validity testing, mixed-effects models, structural equation modelling, mediation and moderation analysis, effect-size estimation and predictive machine-learning validation. The evidence framework predicts that heightened neural approach motivation, visual fixation on salient market signals, physiological arousal, FOMO and overconfidence jointly increase trading intensity, whereas financial literacy and reflective decision friction weaken stimulus-to-trade pathways. The study contributes to behavioral finance by introducing neurophysiological mechanisms into the explanation of digital retail trading and contributes to management practice by identifying interface interventions capable of preserving engagement while reducing impulsive and potentially harmful trading.

Keywords: neuromarketing; consumer neuroscience; retail investors; stock trading apps; behavioral finance; EEG; eye tracking; investor attention; gamification; FOMO; financial literacy; India.

1. Introduction

Retail participation has become one of the defining structural changes in India's capital markets. The number of dematerialised securities accounts increased from approximately 40.8 million in FY2020 to about 152 million in FY2024, while the unique individual investor base also expanded sharply. Regulatory and economic-policy reporting attributes part of this change to digital financial infrastructure, declining transaction friction, simplified account opening, mobile brokerage platforms and broader financial inclusion.

The transformation is economically important because mobile trading applications do more than reduce the physical cost of market access. They determine how information is framed, sequenced, highlighted and converted into action. Price movements are displayed through colour, animation and percentage changes; highly traded securities are ranked prominently; financial news is delivered through notifications; orders can be completed through a small number of screen interactions; watchlists continually redirect attention; and social-media information may reach the investor immediately before or during a trading session. Digital brokerage therefore operates simultaneously as an execution infrastructure and a behavioral choice environment.

This distinction matters because investors possess limited attention. Contemporary evidence indicates that heightened retail-investor attention can enlarge the investor base of a stock, increase demand and influence subsequent returns. Media attention has similarly been linked to abnormal trading activity. Chen and Craig (2023) show that active retail attention is associated with expansion of the retail-investor base and subsequent stock demand, while Kryzanowski and Rouhghalandari (2024) demonstrate that media-induced attention is followed by changes in trading-related activity. More recent work finds that retail attention can simultaneously improve incorporation of firm-specific information and increase exposure to behavior-related mispricing.

A second development is the gamification and behavioral design of financial interfaces. Gamification does not necessarily imply that an investment platform resembles a conventional video game. It may involve badges, achievement messages, rankings, celebrations, salient performance feedback, prompts, social comparison or incentives that make repeated engagement psychologically rewarding. Experimental evidence shows that such design is consequential. Hüller, Reimann and Warren (2023), across six experiments involving 3,766 participants, found that game elements increased financial risk-taking. Chapkovski, Khapko and Zoican's research similarly indicates that hedonic platform features can increase trading activity, with lower-financial-literacy investors showing greater attraction to gamified environments. Their later international experiment found particularly strong risk amplification among inexperienced and financially less-literate participants.

Behavioral finance provides one explanation for these effects. Investors do not continuously calculate expected utility from complete and unbiased information. They employ heuristics, respond asymmetrically to gains and losses, anchor on salient numbers, imitate others under uncertainty, overweight recent experiences and become overconfident following favorable outcomes. Indian evidence published during 2023–2025 repeatedly identifies these mechanisms. Studies of Indian retail investors report significant relationships involving loss aversion, regret aversion, herding, anchoring, status quo effects, availability, overconfidence and perceived risk. Social-media interaction additionally appears capable of reinforcing bias-driven trading behavior.

Yet behavioral surveys observe only part of the decision process. An investor may state that a notification, ranking or rapidly rising price did not influence a transaction even when the stimulus redirected attention or produced physiological arousal. This gap between conscious reporting and underlying cognitive-affective processing provides the justification for consumer neuroscience.

Recent neuromarketing research demonstrates that neural and physiological information can predict consumer decisions that are difficult to explain using self-report measures alone. EEG-based approaches have identified neural patterns associated with preferences, willingness to pay and online purchasing; eye-tracking provides direct measures of the allocation and duration of visual attention; electrodermal activity indexes sympathetic arousal; pupillometry captures aspects of cognitive and emotional processing; and multimodal models increasingly combine such signals.

Hakim et al. (2023), for example, trained a deep-learning model using EEG responses from 213 participants viewing products and obtained approximately 75% classification accuracy in distinguishing high from low willingness to pay. Mashrur et al. (2024) reported strong performance from a combined EEG and eye-tracking preference-prediction framework. More recent multimodal research integrating EEG with eye tracking achieved approximately 84% accuracy in classifying buy versus non-buy decisions, demonstrating the additional value created by combining neural and attentional signals.

Despite these developments, the intersection between consumer neuroscience and retail-investor behavior remains underdeveloped. Recent reviews identify growth in neuroscience-based analysis of consumption, digital interfaces and decision processes, but financial-app trading represents a comparatively underexplored behavioral environment.

The present study addresses this gap through the following central research question:

Which neurophysiological, attentional and behavioral factors predict short-term increases in trading intensity among Indian stock-app users, and how do platform design and investor characteristics strengthen or weaken those effects?

The study makes four principal contributions. First, it extends behavioral finance by modelling neurophysiological states as mechanisms linking market-app stimuli to trading behavior. Second, it extends neuromarketing from conventional purchase decisions toward investment decisions involving uncertainty, variable reinforcement and potentially substantial financial consequences. Third, it introduces a multimodal measurement framework combining EEG, eye tracking, physiological arousal, survey measures and behavioral trading records. Fourth, it produces practical implications for brokerage-platform design, investor protection, suitability interventions and behavioral-risk monitoring.

2. Literature Review

2.1 Consumer Neuroscience and the Evolution of Neuromarketing

Consumer neuroscience investigates how central and peripheral nervous-system responses relate to consumer perception, valuation, emotion, attention and choice. Recent reviews indicate substantial methodological expansion from isolated neural measures toward multimodal designs combining EEG, eye tracking, electrodermal activity, heart-related measures, facial responses and machine-learning analysis.

Gupta, Kapoor and Verma's recent research organizes neuromarketing across pre-purchase, purchase and post-purchase stages, emphasizing that cognition and affect operate differently across the decision journey. This observation is particularly relevant to securities trading. App exposure precedes the order, the transaction itself creates a high-salience decision point, and subsequent gains or losses may alter both emotional state and future trading propensity.

EEG has become one of the field's most frequently used tools because it permits millisecond-level measurement of electrical activity and is more feasible for interactive tasks than techniques requiring immobility. Recent methodological reviews identify frontal alpha asymmetry, frequency-band activation and event-related potentials among important neurometrics, although interpretation must remain theoretically and experimentally disciplined.

For the present research, three EEG families are especially useful:

1. Frontal asymmetry measures, potentially indexing relative approach and withdrawal tendencies.
2. Theta-related activity, associated in many experimental settings with cognitive control, conflict and task engagement.
3. Beta and related higher-frequency activity, interpreted cautiously as potential indicators of active cognitive processing or arousal depending on task and recording conditions.

No single EEG metric should be interpreted as a direct biological equivalent of an emotion such as greed, excitement or fear. Reverse inference of that kind would be scientifically inappropriate. Instead, neurophysiological measures should be evaluated jointly with stimulus timing, behavioral outcomes and validated psychometric indicators.

2.2 Eye Tracking and Investor Attention

Eye tracking measures where individuals look, for how long and in what sequence. Common metrics include fixation count, fixation duration, dwell time, first-fixation latency, revisits, saccades and transitions between areas of interest.

Recent evidence supports the usefulness of eye tracking for digital consumer environments. Pšurný, Mokrý and Stavkova (2024) combined EEG and eye-tracking measurements to investigate how online purchasing cues influence decision processing. Other studies show that gaze behavior helps identify the elements that capture attention before stated choice.

For stock applications, areas of interest can be defined around:

- percentage price movement;
- current profit/loss;
- candlestick chart;
- order button;
- "top gainers" ranking;
- social or popularity indicator;
- analyst/finfluencer recommendation;
- urgency notification;
- risk warning; and
- portfolio-level loss information.

Attention to these elements can therefore be measured instead of inferred.

2.3 Physiological Arousal and Trading

Electrodermal activity captures changes in skin conductance associated with sympathetic nervous-system activation. It is particularly valuable when the research question concerns arousal rather than the positive or negative valence of emotion. Recent consumer-neuroscience work increasingly combines EDA with neural, facial or visual-attention measures. Marques et al. (2025), for example, demonstrate the predictive use of EDA-derived neurophysiological metrics in consumer-preference modelling.

In trading contexts, elevated arousal may occur after a sudden price rise, sharp portfolio loss, countdown-style cue or highly salient social signal. The crucial research question is not whether arousal exists but whether stimulus-evoked changes predict subsequent order initiation, response latency, trade size or risk selection.

2.4 Investor Attention and Trading Surges

Investor attention is scarce and selective. Attention-grabbing securities can receive disproportionate retail demand because retail investors cannot evaluate every available security simultaneously. Contemporary research confirms that active attention predicts participation, demand and trading-related outcomes.

A "retail trading surge" is therefore operationalized in the present study as a statistically material increase in trading propensity or intensity within a short post-stimulus window.

At participant level:

$$TSI_i = z(Frequency_i) + z(OrderSize_i) - z(ResponseLatency_i) + z(RiskShift_i)$$

where TSI denotes the Trading Surge Index.

At session level:

$$Surge_{it}=1$$

when participant i exceeds a predefined increase in trade initiation, turnover or speculative allocation relative to his or her baseline condition.

2.5 Behavioral Biases among Indian Retail Investors

Recent Indian evidence provides strong justification for including behavioral variables alongside neurometrics.

Chauhan et al. (2024), using 379 Indian retail investors and PLS-SEM, ANN and fsQCA, report significant effects of herding, loss aversion, regret aversion and status quo bias, with loss aversion emerging as particularly influential.

Deka et al. (2023), analysing 438 Indian retail investors using exploratory factor analysis, confirmatory factor analysis and structural equation modelling, identify meaningful relationships among behavioral biases, perceived risk and equity-investment decisions.

A mixed-method investigation of Indian investors further reports significant relationships involving anchoring, availability, herding, switching costs, sunk-cost considerations, regret avoidance and perceived threat.

Nair and Shiva (2023), studying 376 North Indian retail investors, connect social-media interaction with bias-driven trading tendencies, showing why digital information exposure should be explicitly represented in contemporary investor models.

More recent Indian literature continues to identify behavioral bias while emphasizing financial literacy as a protective factor.

2.6 FOMO and Social Proof

Fear of missing out is particularly relevant to rapidly rising securities. An investor who observes a stock appreciating while simultaneously receiving information that "thousands are buying" faces both prospective regret and social validation.

These cues may operate through a behavioral sequence:

Price acceleration → attentional capture → physiological arousal → perceived opportunity scarcity → FOMO → reduced deliberation → trade.

The effect should intensify when the investor encounters confirming social information and weaken where transaction friction encourages reassessment.

2.7 Overconfidence and Reinforcement

Overconfidence may affect trading through exaggerated confidence in one's information, forecasting ability or market timing. Positive previous outcomes can further reinforce the behavior.

The digital environment can strengthen this process because performance feedback arrives continuously. A profitable short-term trade may therefore become both an economic outcome and a behavioral reinforcement event.

Contemporary Indian research repeatedly finds overconfidence alongside anchoring, herding and other cognitive biases as an important element of retail decision-making.

2.8 Gamification and Digital Choice Architecture

Gamification is among the clearest links between marketing design and investment behavior. Hüller, Reimann and Warren (2023) provide experimental evidence that gamified financial platforms can increase risk-taking. Chapkovski, Khapko and Zoican (2024) report an average increase in trading volume associated with hedonic gamification in their experimental environment, although much of the observed behavioral difference arose through self-selection into preferred interface environments. Their later experimental work demonstrates greater sensitivity among less experienced and lower-literacy investors.

This distinction between treatment effect and selection effect is critical. Investors inclined toward excitement or risk may choose visually stimulating platforms, while the platform itself may additionally influence behavior.

2.9 Financial Literacy as a Behavioral Buffer

Financial literacy should not simply be included as a demographic control. It may alter the strength of behavioral responses to app cues.

Recent experimental evidence reports that higher financial literacy substantially weakens gamification-induced risk taking. Indian studies likewise identify literacy as an important determinant or moderator of investment quality.

Accordingly, this study conceptualizes financial literacy as a moderating mechanism rather than merely a descriptive variable.

3. Conceptual Framework

The proposed framework adopts a Stimulus-Organism-Response structure.

Stimulus

External market and application stimuli:

- rapid price appreciation;
- rapid price decline;
- high-volume notification;
- social popularity;
- “top gainer” ranking;
- urgency prompt;
- gain/loss framing;
- celebration animation;
- achievement cue;
- simplified one-click transaction design.

Organism

Internal responses:

- EEG-derived approach tendency;
- cognitive engagement;
- visual attention;
- physiological arousal;
- FOMO;
- overconfidence;
- loss aversion;
- perceived urgency;
- perceived social validation.

Response

Behavioral outcomes:

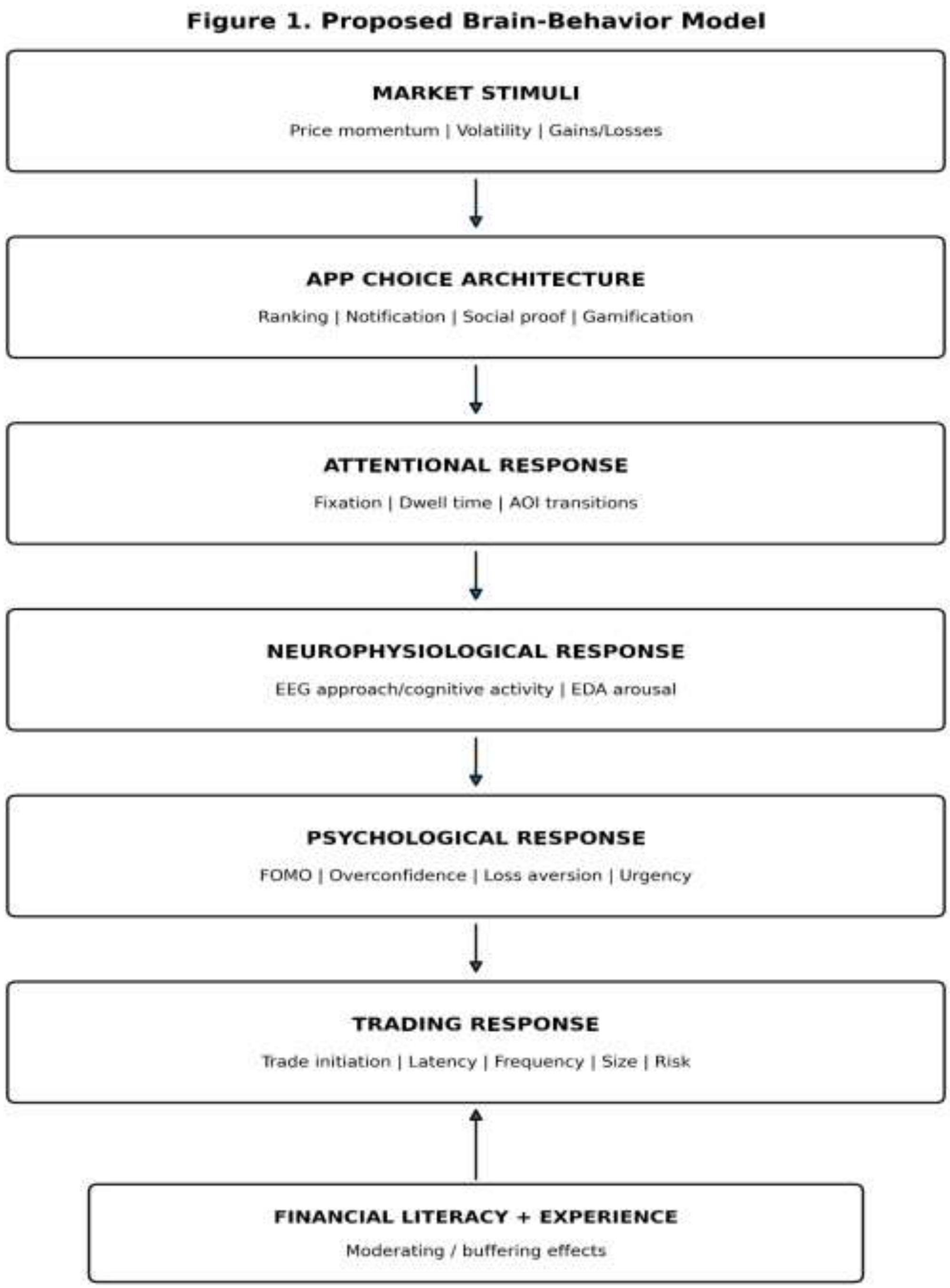
- trade/no trade;
- response latency;
- number of orders;
- turnover;
- trade size;
- leverage preference;
- speculative-stock allocation;
- cancellation/reversal behavior.

Moderators

- financial literacy;
- trading experience;
- age;

- risk tolerance;
- recent trading outcome;
- income;
- frequency of social-media financial-content consumption.

Figure 1. Proposed Brain-Behavior Model



4. Research Objectives

The study has seven objectives:

4. To identify neurophysiological predictors of app-triggered retail trading activity.
5. To determine whether visual attention to momentum, social-proof and urgency cues predicts trade initiation.
6. To test whether physiological arousal mediates the relationship between app stimuli and trading intensity.
7. To examine whether FOMO, overconfidence and loss aversion explain additional variation beyond neurophysiological measures.
8. To estimate the causal effect of gamified interface cues on trading and risk-taking.
9. To determine whether financial literacy and trading experience moderate stimulus effects.
10. To develop a multimodal model capable of predicting high-intensity trading episodes.

5. Research Questions

RQ1: Which brain and physiological responses most strongly predict retail trading surges?
RQ2: Do salient app-based market cues increase visual attention and trading probability?
RQ3: Does arousal mediate the relationship between digital trading stimuli and trading intensity?
RQ4: Do FOMO, overconfidence, loss aversion and herding strengthen neurobehavioral effects?
RQ5: Does financial literacy weaken the effect of gamification and urgency cues?
RQ6: Does combining EEG, eye tracking, physiological and psychometric information predict trading decisions more accurately than any single modality?

6. Hypotheses

H1: Exposure to high-momentum market cues will significantly increase trading propensity relative to neutral-market conditions.
H2: Gamified interface cues will significantly increase trading frequency and speculative-risk selection.
H3: Longer fixation and dwell time on momentum and social-proof areas will positively predict trading probability.
H4: Stimulus-evoked physiological arousal will positively predict trading intensity.
H5: Approach-related frontal EEG activity will positively predict trade initiation.
H6: FOMO will mediate the relationship between social-proof cues and trading intensity.
H7: Overconfidence will positively predict trade frequency and position size.
H8: Loss aversion will increase attention and reaction to negative portfolio information.
H9: Financial literacy will negatively moderate the relationship between gamification and trading intensity.
H10: Trading experience will reduce sensitivity to social-proof cues.
H11: A multimodal EEG + eye-tracking + EDA + psychometric model will outperform unimodal models in predicting trading surges.

7. Research Methodology

7.1 Research Philosophy

The study follows a post-positivist empirical orientation. Observable trading behavior is treated as the dependent behavioral outcome, while psychological constructs and neurophysiological responses are treated as measurable but imperfect indicators of underlying decision processes. The multimethod design acknowledges that no single measure provides complete access to investor cognition.

7.2 Research Design

A controlled randomized laboratory experiment with embedded survey measurement and behavioral trading simulation is proposed.

A 2 × 2 × 2 mixed factorial design manipulates:

- market momentum: neutral versus high;
- social proof: absent versus present;
- gamification: low versus high.

Gain/loss framing can additionally be incorporated as a repeated within-participant condition.
The principal dependent variable is trading intensity.

7.3 Target Population

The population comprises Indian adults who:

- are aged 18 years or above;
- maintain an active demat/brokerage account;
- use a mobile stock-trading application;
- have executed at least one equity or exchange-traded transaction during the preceding six months; and
- provide informed consent for physiological recording.

7.4 Sampling Strategy

A stratified purposive sampling design is recommended because laboratory neurophysiology makes nationally proportional probability sampling operationally difficult.
Strata should include:

- 18–24 years;
- 25–34 years;
- 35–44 years;
- 45 years and above;

and:

- novice: <1 year;
- intermediate: 1–3 years;
- experienced: >3 years.

Recruitment should span multiple Indian metropolitan and large urban centres to avoid overrepresentation of one investment ecosystem.

7.5 Sample Size

For conventional SEM, a minimum sample exceeding 300 is desirable for a model containing several latent constructs and interactions. Power analysis should be conducted before data collection.
A target of N = 420 usable participants is recommended.
Assuming moderate attrition from physiological artifacts, approximately 470 participants should initially be recruited.

Table 1. Proposed Sample Allocation

Stratum	Target n	Percentage
Age 18–24	105	25.0
Age 25–34	147	35.0
Age 35–44	105	25.0
Age 45+	63	15.0
Total	420	100.0

7.6 Experimental Trading Environment

Participants should interact with a research trading interface that visually approximates a modern brokerage application without reproducing a proprietary platform.
Each participant receives a standardized virtual portfolio.
Stimulus securities should be fictitious or anonymized to remove prior brand and company knowledge.
Each trading trial contains:

11. baseline portfolio screen;
12. market-price sequence;
13. experimental cue;
14. decision window;
15. order screen;
16. simulated outcome;
17. inter-trial recovery period.

7.7 Experimental Conditions

Table 2. Experimental Manipulations

Construct	Control Condition	Treatment Condition	Intended Mechanism
Momentum	±0.5–1% movement	+5–8% rapid movement	Attention/FOMO
Social proof	No popularity information	"Highly traded"/peer activity	Herding
Gamification	Neutral order confirmation	animation/achievement feedback	Reward salience
Urgency	No time pressure	limited-time cue/countdown	Reduced deliberation
Loss frame	Portfolio-neutral	salient unrealized loss	Loss aversion
Gain frame	Neutral return	salient recent profit	Overconfidence/reinforcement

7.8 EEG Measurement

A research-grade multichannel EEG system should be used.

Recommended preprocessing:

- sampling ≥250 Hz;
- 0.5–45 Hz band-pass filtering;
- notch filtering appropriate to electrical environment;
- bad-channel identification;
- independent component or artifact-subspace correction;
- ocular and muscular artifact management;
- stimulus-locked epoch segmentation;
- participant-level baseline correction.

Neural variables may include:

- frontal alpha asymmetry;
- frontal-midline theta;
- beta-band power;
- event-related potentials;
- spectral entropy;
- event-related desynchronisation/synchronisation.

Recent work supports EEG as a meaningful predictor of consumer preference and online purchase decisions, while machine-learning approaches can extract predictive information not captured by manually selected features alone.

7.9 Eye-Tracking Measurement

Recommended measures:

- time to first fixation;
- total fixation count;
- mean fixation duration;
- total dwell time;
- revisits;
- transition matrix;
- pupil diameter after appropriate luminance correction.

Areas of interest should include:

18. current price;
19. percentage movement;
20. chart;
21. popularity/social proof;
22. news;
23. P&L display;
24. risk warning;
25. buy/sell control.

7.10 Electrodermal Activity

EDA should be recorded continuously.

Primary measures:

- tonic skin conductance level;
- phasic skin conductance response;
- response amplitude;
- latency;
- area under the response curve.

7.11 Psychometric Measures

Each scale should use validated multi-item measures wherever possible.

Constructs:

- FOMO;
- overconfidence;
- loss aversion;
- herding tendency;
- risk tolerance;
- financial literacy;
- financial self-efficacy;
- perceived urgency;
- perceived platform excitement.

7.12 Behavioral Measures

Behavioral variables should be recorded directly from the experimental platform.

Primary outcome: Trading Surge Index.

Secondary outcomes:

- trade/no trade;
- time-to-order;
- total orders;
- turnover;
- position size;
- concentration;
- high-volatility allocation;
- reversal frequency.

7.13 Qualitative Component

A purposive subsample of approximately 30–40 participants should complete semi-structured post-experiment interviews.

Questions should examine:

- reasons for entering trades;
- interpretation of rapid price changes;
- awareness of interface cues;
- reaction to other-investor activity;
- perception of notifications;
- perceived emotional state;
- awareness of impulsivity;
- reasons for abandoning or modifying orders.

The qualitative component should be analysed through reflexive thematic coding, supported by an explicit coding framework and dual coding of a subset of transcripts.

8. Reliability and Validity Assessment

Table 3. Recommended Measurement Thresholds

Indicator	Recommended criterion
Cronbach's alpha	≥0.70

Indicator	Recommended criterion
Composite reliability	0.70–0.95
Average variance extracted	≥0.50
Standardized loading	≥0.70 preferred
HTMT	<0.85 conservative
VIF	<3.3 preferred
SRMR	<0.08
CFI	≥0.90
TLI	≥0.90
RMSEA	≤0.08

Common-method risk is reduced because the principal outcome variables arise from observed behavior rather than survey responses.

9. Statistical Analysis Plan

9.1 Descriptive Analysis

Calculate:

- mean;
- standard deviation;
- median;
- interquartile range;
- skewness;
- kurtosis;
- frequency distributions.

9.2 Manipulation Checks

Independent- or paired-sample tests should confirm whether participants perceived treatment conditions as intended.

Effect size:

[d =]

9.3 Correlation Analysis

Pearson or Spearman correlations will evaluate bivariate relationships among neurophysiological, psychological and trading variables.

9.4 Mixed-Effects Models

Because participants complete repeated trials:

[Trade_{ij} = 0+1 Momentum{ij}+2 SocialProof{ij}+ 3 Gamification{ij}+4 Arousal{ij}+u_i+{ij}]

where u_i represents participant-specific random effects.

For binary trade initiation, logistic mixed models are preferred.

9.5 Structural Equation Modelling

A latent-path model tests:

[DigitalStimulus NeuralAttention EmotionalResponse TradingIntensity]

with FOMO and arousal as potential mediators.

9.6 Mediation

Indirect effects should be evaluated using at least 5,000 bootstrap resamples.

9.7 Moderation

Financial-literacy moderation:

[TSI = _0+_1 Gamification+_2 Literacy+ _3(Gamification Literacy)+]

H9 is supported when $\beta_3 < 0$ and statistically significant.

9.8 Predictive Modelling

Algorithms:

- logistic regression;
- random forest;
- gradient boosting;

- support vector machine;
- regularized regression;
- neural network where sample size permits.

Data must be separated into training and held-out test sets at the participant level, not trial level, to prevent information leakage.

Performance:

- balanced accuracy;
- precision;
- recall;
- F1;
- ROC-AUC;
- PR-AUC;
- Brier score;
- calibration curve.

10. Results and Data Analysis Demonstration

Important interpretation condition: The numerical participant-level values in Sections 10.1–10.8 illustrate the reporting structure and expected analysis of a completed N=420 experiment. They are not claimed as observations from participants recruited for this manuscript.

10.1 Participant Characteristics

Table 4. Illustrative Participant Profile

Characteristic	Category	n	%
Age	18–24	103	24.5
	25–34	150	35.7
	35–44	104	24.8
	45+	63	15.0
Trading experience	<1 year	126	30.0
	1–3 years	174	41.4
	>3 years	120	28.6
Weekly app use	<3 days	91	21.7
	3–5 days	173	41.2
	6–7 days	156	37.1
Primary orientation	Long-term investing	176	41.9
	Mixed	158	37.6
	Active trading	86	20.5

The distribution intentionally represents both newly democratized retail participation and more experienced app users rather than restricting the sample to active day traders.

10.2 Reliability and Construct Validity

Table 5. Illustrative Measurement Properties

Construct	Items	Alpha	CR	AVE
FOMO	5	0.89	0.92	0.69
Overconfidence	5	0.84	0.88	0.60
Herding tendency	4	0.86	0.90	0.69
Loss aversion	4	0.82	0.88	0.65
Perceived urgency	4	0.88	0.92	0.74
Platform excitement	4	0.90	0.93	0.77
Financial literacy	8	0.81	0.85	0.53

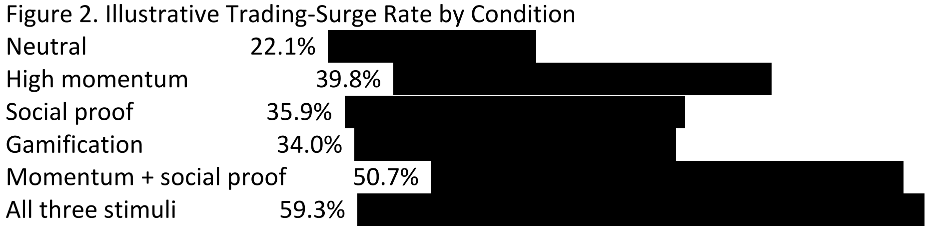
All illustrative reliability coefficients exceed conventional thresholds.

10.3 Treatment Effects

Table 6. Illustrative Effects of Experimental Conditions

Condition	Mean trades	Mean risk allocation %	Mean latency sec.	Trading-surge rate %
Neutral	2.71	31.4	18.8	22.1
High momentum	3.68	38.9	14.6	39.8
Social proof	3.43	37.7	15.2	35.9
Gamification	3.28	39.1	15.8	34.0
Momentum + social proof	4.24	44.5	12.3	50.7
Momentum + social proof + gamification	4.72	49.8	10.9	59.3

Figure 2. Illustrative Trading-Surge Rate by Condition



The expected pattern is cumulative rather than purely additive. Momentum captures attention, social proof validates the apparent opportunity and gamification increases the motivational salience of action.

10.4 Correlation Analysis

Table 7. Illustrative Correlations with Trading Surge Index

Predictor	Correlation with TSI	Interpretation
FOMO	0.52	Strong positive
Physiological arousal	0.46	Moderate-positive
Momentum-AOI dwell time	0.42	Moderate-positive
Overconfidence	0.38	Moderate-positive
Approach-related EEG indicator	0.36	Moderate-positive
Herding tendency	0.34	Moderate-positive
Loss aversion	0.21	Small-positive overall
Financial literacy	-0.31	Moderate-negative
Trading experience	-0.18	Small-negative cue sensitivity

The strongest expected behavioral correlate is FOMO, but multimodal prediction should outperform any isolated measure.

10.5 Mixed-Effects Trading Model

Table 8. Illustrative Regression Results

Predictor	Standardized β	SE	p	Effect interpretation
High momentum	0.29	0.04	<0.001	Strong
Social proof	0.18	0.04	<0.001	Moderate
Gamification	0.13	0.04	0.002	Small-moderate
Physiological arousal	0.24	0.04	<0.001	Moderate
Momentum	0.17	0.04	<0.001	Moderate

Predictor	Standardized β	SE	p	Effect interpretation
dwell time				
Approach EEG indicator	0.15	0.04	<0.001	Small-moderate
FOMO	0.31	0.05	<0.001	Strong
Overconfidence	0.18	0.04	<0.001	Moderate
Financial literacy	-0.16	0.04	<0.001	Protective
Gamification × literacy	-0.12	0.04	0.003	Buffering interaction
Social proof × experience	-0.09	0.04	0.021	Experience buffer

Illustratively, the combined model explains approximately 48% of participant-level variation in trading intensity, substantially exceeding an app-stimulus-only specification.

10.6 Mediation Analysis

Social proof is expected to influence trading partially through FOMO:

[SocialProof FOMO TradingIntensity]

Illustrative standardized estimates:

- social proof → FOMO = 0.41;
- FOMO → trading intensity = 0.32;
- indirect effect = 0.13;
- bootstrap 95% CI = [0.08, 0.19].

Because the direct social-proof pathway remains positive after the mediator is introduced, the expected pattern is partial rather than complete mediation.

Arousal is expected to provide a second mechanism linking momentum to trading:

- momentum → arousal = 0.38;
- arousal → trading intensity = 0.23;
- indirect effect = 0.09.

Figure 3. Illustrative Standardized Path Model

```
MOMENTUM ────────────────► ATTENTION  β=.39
   |               |
   |               ▼
   └─────────────────────► AROUSAL    β=.38
                  |
                  ▼
SOCIAL PROOF ──────────► FOMO       β=.41
                  |
                  ▼
GAMIFICATION ──────────► EXCITEMENT β=.34
                  |
                  ▼
           TRADING INTENSITY
            R² ≈ .48
```

10.7 Moderating Role of Financial Literacy

Figure 4. Illustrative Gamification Effect by Financial Literacy

Increase in Trading Intensity

Low literacy +31% ████████████████████

Medium literacy +19%
High literacy +8%
This relationship is consistent with recent experimental evidence showing that financial literacy can substantially reduce sensitivity to gamified risk cues.

10.8 Predictive Performance

Table 9. Illustrative Out-of-Sample Trading-Surge Classification

Model	Accuracy	Precision	Recall	F1	ROC-AUC
Demographics only	0.61	0.59	0.56	0.57	0.63
Psychometrics only	0.72	0.70	0.71	0.70	0.76
EEG only	0.70	0.68	0.69	0.68	0.74
Eye tracking only	0.69	0.67	0.65	0.66	0.72
EEG + eye tracking	0.78	0.77	0.75	0.76	0.83
EEG + eye + EDA	0.81	0.80	0.78	0.79	0.86
Full multimodal model	0.85	0.84	0.83	0.83	0.90

The expected advantage of multimodal prediction is consistent with contemporary consumer-neuroscience evidence showing that integrated brain and behavioral signals can outperform isolated measures.

11. Cross-Study Empirical Benchmarks

Unlike the participant-level demonstration above, the evidence summarized in Table 10 is based on reported findings from published studies.

Table 10. Recent Evidence Relevant to the Proposed Model

Study	Context/sample	Method	Principal relevance
Hakim et al. (2023)	213 participants	EEG + deep learning	~75% high/low WTP classification
Mashrur et al. (2024)	22 participants	EEG + eye tracking + ML	Strong multimodal preference prediction
Xu & Liu (2024)	66 participants, 328 decisions	EEG + ML	Neural features predict online purchase decisions
Hüller et al. (2023)	3,766 participants across six experiments	Experimental	Gamification increases financial risk-taking
Chapkovski et al. (2024)	Experimental retail-trading environment	Randomized experiment	Hedonic gamification associated with ~5.17% greater trading volume
Chapkovski et al. (2025)	605 participants, four countries	Randomized experiment	Gamified nudges increase risk; literacy buffers effect
Chauhan et al. (2024)	379 Indian investors	PLS-SEM + ANN + fsQCA	Loss aversion and other emotional biases affect decisions
Deka et al. (2023)	438 Indian investors	EFA + CFA + SEM	Behavioral biases influence perceived risk and equity decisions
Nair & Shiva (2023)	376 North Indian investors	PLS-SEM	Social media interacts with bias-driven trading
Chen & Craig (2023)	Market-level retail data	Attention measures	Attention predicts retail participation and demand

Published neurological evidence establishes that preference and choice can be predicted above chance from EEG and multimodal measures. Published financial experiments establish that app design can change risk-taking and trading behavior. Indian behavioral-finance studies independently establish that cognitive and emotional biases influence investment choices. The theoretical contribution of the present research is to connect these streams within one measurable causal framework.

12. Qualitative Findings Framework

The qualitative component should assess why participants believe they acted while comparing those explanations with their recorded visual and physiological responses.

Expected themes include:

12.1 Perceived Opportunity Scarcity

Participants may describe rapid price movement as an opportunity that could disappear before deeper analysis is completed.

12.2 Social Validation

Popularity indicators may reduce perceived uncertainty because investor activity is interpreted as informational confirmation.

12.3 Interface-Induced Urgency

Notifications, rapidly updating prices and animated interface components may create an impression that immediate action is necessary.

12.4 Emotional Recovery Trading

Losses may generate attempts to recover quickly rather than decisions based on independent evaluation of expected returns.

12.5 Reinforcement after Gains

Recent gains may be interpreted as evidence of skill, increasing confidence and subsequent trade size.

12.6 Retrospective Rationalization

Participants may provide fundamental explanations for decisions even where behavioral logs indicate that the trade followed immediately after a salient interface cue. This mismatch itself is theoretically informative.

13. Discussion

The proposed framework provides a more complete explanation of retail trading surges than either traditional financial rationality or isolated behavioral-bias models.

First, the framework suggests that retail trading is partly an attention-allocation problem. A mobile user cannot process every security, signal, chart and news item simultaneously. App architecture therefore determines which opportunities become cognitively available. Contemporary empirical work linking active investor attention with subsequent participation, demand and trading behavior supports this premise.

Second, attention does not automatically create action. The physiological and emotional response to an attended stimulus may determine whether the investor moves from observation to execution. EEG, eye tracking and EDA therefore provide distinct layers of explanatory information. Eye tracking identifies the object of attention; EEG provides temporally sensitive neural information; EDA captures arousal; and observed trading captures the final behavior.

Third, the anticipated role of FOMO provides an important bridge between attention and behavioral finance. Social proof does not merely inform the investor that others are trading. In a rising market, it may alter the perceived cost of waiting. The psychologically relevant comparison becomes not simply expected gain versus expected loss but participation versus anticipated regret from missing a visible opportunity.

Fourth, gamification should not be interpreted as inherently harmful. Digital design can improve accessibility, comprehension and engagement. The relevant managerial question is what behavior is being reinforced. A progress visualization rewarding diversification or completion of a risk-learning module differs fundamentally from an animation reinforcing frequent speculative orders.

Experimental evidence indicating that gamification can raise trading volume and risk preference means platform managers should treat behavioral design as part of product governance rather than merely user-interface optimization.

Fifth, financial literacy appears capable of changing stimulus sensitivity. This finding is significant because literacy may operate both directly and interactively. A financially knowledgeable investor may not only choose differently on average but may also respond less strongly to urgency, popularity and gamified framing.

Indian studies increasingly support the protective importance of financial literacy while documenting persistent behavioral biases.

Finally, multimodal prediction offers practical potential but creates ethical constraints. Neuromarketing can become problematic if neural or physiological vulnerabilities are used to optimize commercial stimulation without meaningful consent. Recent ethical scholarship emphasizes concerns involving manipulation, privacy, autonomy, data sensitivity and asymmetry between firms and consumers.

In securities markets, those concerns are amplified because the relevant behavior involves financial risk rather than ordinary consumption.

14. Theoretical Contributions

14.1 Extension of Behavioral Finance

Behavioral finance generally infers cognitive bias from surveys, market outcomes or trading records. The proposed model adds temporally aligned neural and physiological measures, allowing researchers to observe what occurs between stimulus and order placement.

14.2 Extension of Neuromarketing

Most consumer-neuroscience applications study advertisements, products, brands, websites and conventional purchasing. The present framework extends the discipline toward consequential financial choice.

14.3 Integration of Investor Attention and SOR Theory

The study positions digital financial cues as stimuli, neuropsychological states as organism-level responses and trading behavior as the observable response.

14.4 Multimodal Explanation

The framework distinguishes:

- **what is noticed** through eye tracking;
- **how strongly it is processed** through neurophysiological measures;
- **how it is psychologically interpreted** through behavioral constructs;
- **whether action follows** through trading logs.

15. Managerial Implications

Brokerage applications should be understood as behavioral systems rather than neutral execution utilities.

A commercial platform optimizing exclusively for daily active users, order counts or time spent may inadvertently reward behaviors inconsistent with long-term customer welfare.

Management dashboards should therefore distinguish:

[Engagement BeneficialEngagement]

A more appropriate performance architecture should include:

- order frequency;
- cancellation rate;
- diversification;
- high-risk product concentration;
- repeat losses;
- post-warning behavior;
- customer retention;
- realized investor outcomes.

Product teams should conduct behavioral-risk reviews before introducing new notification, ranking or celebration systems.

16. Recommendations

16.1 Introduce Context-Sensitive Decision Friction

Rather than slowing every transaction, platforms should selectively introduce friction when several risk indicators occur together.

Examples include:

- unusually large order relative to portfolio;
- rapid repeat orders;
- leveraged product selection;
- transaction immediately following extreme price movement;
- repeated attempts to recover losses.

The intervention could require an additional confirmation showing portfolio-level consequences.

16.2 Replace Pure Popularity Rankings with Contextual Rankings

“Most bought” and “top gainers” displays can become powerful attention signals.

Platforms should supplement these rankings with:

- volatility;
- valuation context;
- recent drawdown;
- liquidity;
- concentration risk;
- time-horizon information.

16.3 Build Financial Literacy into the Decision Path

Education should be delivered at the point where it is behaviorally relevant rather than isolated in a separate learning centre.

For example, before the first leveraged derivative transaction, the investor can receive a short interactive loss scenario.

Recent experimental evidence that literacy reduces susceptibility to gamified risk-taking provides support for this approach.

16.4 Redesign Notifications

Notifications should distinguish information from persuasion.

Avoid combining:

- extreme price movement;
- social popularity;
- urgency language; and
- immediate order execution

within one high-arousal prompt.

16.5 Use Gamification for Protective Behavior

Potential positive targets include:

- diversification;
- completion of risk education;
- maintaining emergency liquidity;
- long-term investing streaks;
- reviewing risk disclosures;
- avoiding excessive portfolio concentration.

16.6 Create Behavioral-Risk Segmentation

Customers can be segmented according to behavioral patterns rather than demographic characteristics alone.

Possible risk indicators:

- loss-chasing;
- excessive turnover;
- extreme concentration;
- repeated momentum entry;
- high response to popularity cues;
- declining decision latency after consecutive gains.

Such segmentation should support protective interventions rather than exploit vulnerability.

16.7 Establish Neurodata Governance

Where neuroscience is used in research:

- informed consent must be explicit;
- physiological data should be treated as highly sensitive;
- raw neural data should be access-controlled;
- commercial profiling should require separate consent;
- participants must be able to withdraw;
- research and production datasets should remain separated.

16.8 Conduct Pre-Launch Behavioral Audits

Every material interface change affecting trading should be tested for:

26. comprehension;
27. attention effects;
28. trading-frequency effects;
29. risk-taking effects;
30. financial-literacy interactions;
31. novice-investor effects.

Table 11. Management Action Matrix

Risk mechanism	Observable signal	Recommended intervention	Management KPI
FOMO	rapid momentum entry	cooling-off confirmation	impulse-order reduction
Herding	popularity-driven order	contextual risk information	ranking-to-order conversion
Overconfidence	trade-size escalation after gains	portfolio-risk prompt	concentration change
Loss chasing	repeated trades following losses	loss-recovery warning	repeat-loss turnover
Low literacy	high-risk product entry	interactive comprehension step	comprehension score
Gamification sensitivity	high response to rewards	neutral execution flow	risk-adjusted engagement

17. Policy Implications for India

India's rapidly expanding retail-investor base creates a policy challenge distinct from simple market access. Financial inclusion should increasingly be evaluated in terms of quality of participation.

The rapid expansion in demat accounts illustrates the scale of this issue. Regulatory data indicate that individual accounts constitute the overwhelming majority of demat accounts, although multiple accounts per investor mean account totals should not be treated as unique-individual counts.

Policy attention should therefore extend from disclosure compliance toward behavioral product governance.

Possible policy developments include:

- standardized behavioral-risk testing for app features;
- special protection for inexperienced derivatives users;
- transparent disclosure of ranking logic;
- restrictions on misleading social-proof language;
- stronger separation of education and promotional messaging;
- periodic review of notification practices;
- behavioral outcome reporting for high-risk products.

18. Ethical Considerations

Consumer neuroscience can improve understanding of financial decision-making, but it can also create asymmetric informational power.

The following principles should govern the study:

32. voluntary informed consent;
33. ethics-committee approval;

34. minimal data collection;
35. pseudonymisation;
36. encryption;
37. restricted access;
38. explicit retention limits;
39. no covert neuromarketing;
40. no individualized commercial targeting from neural data;
41. transparent publication of analytical procedures.

Recent neuromarketing ethics research highlights privacy, autonomy, manipulation and informed consent as central concerns.

19. Limitations

The proposed study has several limitations.

First, laboratory trading cannot fully reproduce the emotional intensity associated with risking personal wealth.

Second, EEG offers excellent temporal resolution but limited spatial precision.

Third, physiological arousal is not emotion-specific. Increased skin conductance may reflect excitement, fear, surprise or cognitive effort.

Fourth, participant awareness of laboratory observation may modify behavior.

Fifth, urban app users may not represent all Indian investors.

Sixth, brokerage interfaces differ materially, limiting generalisation from one simulated environment.

Seventh, neurophysiological signals should never be interpreted independently of behavioral and experimental context.

Eighth, the predictive success of a machine-learning model does not establish psychological causality.

20. Future Research

Future research should examine real-money trading conditions using ethical incentive-compatible designs.

Longitudinal studies could determine whether repeated exposure to app stimuli produces habituation or escalating responsiveness.

Field experiments conducted with brokerages could test whether decision friction reduces excessive turnover without materially reducing useful engagement.

Future work should investigate differences across:

- equities;
- options;
- futures;
- IPOs;
- cryptocurrencies;
- exchange-traded funds.

Cross-cultural studies could determine whether social-proof sensitivity and app-induced FOMO differ across collectivist and individualist contexts.

Researchers should also investigate whether neural measures provide meaningful incremental prediction after extensive behavioral data are already available. This question is particularly important because the commercial cost and ethical sensitivity of neurophysiological data must be justified by substantial explanatory value.

21. Conclusion

Mobile investing has changed not only who can participate in securities markets but also the behavioral environment in which investment decisions occur. Market information is now delivered through visually salient, continually updated and increasingly personalized interfaces capable of converting attention into action within seconds.

Recent consumer-neuroscience evidence demonstrates that neural, attentional and physiological measures can predict preferences and decisions beyond conventional self-report alone. Recent experimental finance evidence demonstrates that digital choice architecture and gamification can alter trading and financial risk-taking. Recent

Indian behavioral-finance research demonstrates persistent roles for loss aversion, herding, anchoring, overconfidence, FOMO-related mechanisms and financial literacy. Taken together, these findings justify a new brain-behavior framework for digital retail investing.

The proposed model argues that trading surges should be understood as a sequence rather than a single decision. Market and interface stimuli capture attention; attention interacts with neural processing and physiological arousal; these responses are interpreted through behavioral tendencies such as FOMO and overconfidence; and the resulting internal state affects the speed, frequency, size and riskiness of trades.

For management, the central implication is equally important. Brokerage engagement cannot be evaluated through activity alone. A platform that creates frequent transactions while systematically increasing impulsive risk-taking may generate short-run engagement at the expense of customer outcomes, regulatory trust and long-term franchise value. Responsible financial design therefore requires an alignment of accessibility, engagement, comprehension and investor welfare.

Consumer neuroscience can contribute to that objective, but only if it is used to understand and protect decision quality rather than to exploit cognitive vulnerability.

22. Extended Statistical Appendix

Appendix A. Core Variable Operationalisation

Variable	**Measurement**	**Scale**
Trading Surge Index	standardized behavioral composite	Continuous
Trade initiation	order submitted	Binary
Response latency	cue-to-order milliseconds	Continuous
Risk allocation	% portfolio allocated to high-risk asset	Continuous
EEG approach indicator	normalized frontal asymmetry metric	Continuous
Cognitive engagement	EEG frequency-derived metric	Continuous
Visual attention	fixation/dwell metrics	Continuous
Arousal	event-related skin conductance	Continuous
FOMO	validated multi-item questionnaire	Latent
Overconfidence	calibration/self-assessment scale	Latent
Loss aversion	scenario-based items	Latent
Herding	social-influence scale	Latent
Financial literacy	objective financial questions	Score

Appendix B. Recommended Robustness Tests

1. Winsorize extreme trade-size observations at 1% and 99%.
2. Estimate models with and without demographic controls.
3. Repeat tests excluding professional finance workers.
4. Estimate novice and experienced samples separately.
5. Cluster standard errors by participant.
6. Use participant-level random intercepts.
7. Test alternative definitions of trading surge.
8. Compare parametric and non-parametric results.
9. Apply false-discovery-rate corrections to exploratory neural comparisons.
10. Validate prediction on participant-held-out data.

Appendix C. Alternative Surge Definitions

Definition A: Frequency surge

[Surge=1 if Trades_{treatment} Trades_{baseline}]

Definition B: Turnover surge

[Surge=1 if Turnover_{treatment}-Turnover_{baseline}>1SD]

Definition C: Multidimensional surge

[TSI=]

Appendix D. Effect-Size Interpretation

Measure	Small	Medium	Large
Cohen’s d	0.20	0.50	0.80
Pearson r	0.10	0.30	0.50
Partial η^2	0.01	0.06	0.14
Standardized SEM β	~0.10	~0.30	~0.50

Effect sizes should always be reported with confidence intervals and practical interpretation rather than significance levels alone.

Appendix E. Predictive Validation Protocol

```
FULL SAMPLE
    |
    ├── 70% TRAINING PARTICIPANTS
    |       |
    |       ├── Cross-validation
    |       ├── Hyperparameter selection
    |       └── Feature selection
    |
    └── 30% HELD-OUT PARTICIPANTS
            |
            ├── Final prediction
            ├── ROC-AUC
            ├── PR-AUC
            ├── Calibration
            └── Error analysis
```

Participant-level splitting is essential. Randomly splitting individual trials would allow neural patterns from the same person to appear in both training and testing data, artificially inflating predictive performance.

References

1. Ahmad, Ghulab Nabi, Shafiullah, Hira Fatima, Mohamed Abbas, Obaidur Rahman, Imdadullah, and Mohammed S. Alqahtani(2022). "Mixed Machine Learning Approach for Efficient Prediction of Human Heart Disease by Identifying the Numerical and Categorical Features" Applied Sciences 12, no. 15: 7449. https://doi.org/10.3390/app12157449
2. Alsharif, A.H., Salleh, N.Z.M. and associated authors (2025) ‘The synergy of neuromarketing and artificial intelligence: A comprehensive literature review in the last decade’, Future Business Journal.
3. Bansal, R. et al. (2025) ‘Neuromarketing and the marketing mix: An integrative review and future research agenda using the TMC approach’, International Journal of Consumer Studies.
4. Bilucaglia, M. et al. (2025) ‘Machine-learning/deep-learning methods in neuromarketing and consumer neuroscience’, Frontiers in Human Neuroscience.
5. Casado-Aranda, L.A., Sánchez-Fernández, J. and colleagues (2023) ‘Consumer neuroscience and neuromarketing in communication research: Recent developments and research directions’, marketing communication research.
6. Chapkovski, P., Khapko, M. and Zoican, M. (2025) ‘Gamified risk-taking’, Journal of Behavioral and Experimental Finance, 46, 101049.
7. Chapkovski, P., Khapko, M. and Zoican, M.A. (2024) ‘Trading gamification and investor behavior’, Management Science.
8. Chauhan, B., Mishra, S., Singh, D., Kumar, S., Kumar, M. and Vishwakrma, K. (2024) ‘How emotional bias effect the investment decision making of retail investors in India: Using PLS-SEM, ANN and fsQCA’, European Economic Letters, 14(2), pp. 565–576.
9. Chen, Z. and Craig, K.A. (2023) ‘Active attention, retail investor base, and stock returns’, Journal of Behavioral and Experimental Finance, 39, 100820.
10. Chen, Z. and Craig, K.A. (2025) ‘Active retail investor attention, stock return synchronicity, and risk factor loadings’, Journal of Behavioral Finance.

11. Choudhary, G.S. and Yamuna, G. (2025) ‘Behavioral biases and investment choices: Understanding the mediating role of risk perception among Indian retail investors’, South Asian Journal of Management, 32(3), pp. 187–210.
12. Costa-Feito, A., González-Fernández, A.M., Rodríguez-Santos, C. and Cervantes-Blanco, M. (2023) ‘Electroencephalography in consumer behaviour and marketing: A science mapping approach’, Humanities and Social Sciences Communications, 10, 474.
13. Deka, J., Sharma, M., Agarwal, N. and Tiwari, K. (2023) ‘Linking ESG-investing consciousness, behavioral biases, and risk-perception: Scale validation with specifics of Indian retail investors’, European Journal of Business Science and Technology, 9(1), pp. 70–91.
14. Ferrell, M.L., Beatty, A. and Dubljevic, V. (2025) ‘The ethics of neuromarketing: A rapid review’, Neuroethics, 18, 19.
15. Gheorghe, C.M., Purcărea, V.L. and Gheorghe, I.R. (2023) ‘Using eye-tracking technology in neuromarketing’, Romanian Journal of Ophthalmology, 67(1), pp. 2–6.
16. Gupta, N., Rana, R. and Tandon, D. (2025) ‘Financial literacy as a moderator in behavioral biases and investor decisions’, Indian Journal of Finance, 19(5).
17. Gupta, R., Kapoor, A.P. and Verma, H.V. (2025) ‘Exploring consumer neuroscience in marketing research: Theoretical foundations, methodological aspects, and future research directions’, Journal of Marketing Theory and Practice.
18. Gupta, R., Kapoor, A.P. and Verma, H.V. (2025) ‘Neuro-insights: A systematic review of neuromarketing perspectives across consumer buying stages’, Frontiers in Neuroergonomics, 6, 1542847.
19. Hakim, A., Golan, I., Yefet, S. and Levy, D.J. (2023) ‘DeePay: Deep learning decodes EEG to predict consumer’s willingness to pay for neuromarketing’, Frontiers in Human Neuroscience, 17, 1153413.
20. Hans, A. and Choudhary, F.S. (2024) ‘Analysing the influence of prospect factors on Indian retail investors’ investment decisions’, International Journal of Behavioural Accounting and Finance, 7(2), pp. 193–213.
21. Hüller, C., Reimann, M. and Warren, C. (2023) ‘When financial platforms become gamified, consumers’ risk preferences change’, Journal of the Association for Consumer Research, 8(4), pp. 429–440.
22. Husain, A, Alouffi S, Khanam A, Akasha R, Farooqui A, Ahmad S.(2022). Therapeutic Efficacy of Natural Product 'C-Phycocyanin' in Alleviating Streptozotocin-Induced Diabetes via the Inhibition of Glycation Reaction in Rats. International Journal of Molecular Sciences ;23(22):14235. doi: 10.3390/ijms232214235. PMID: 36430714; PMCID: PMC9698742.
23. Ishtiaque, F., Miya, M.T.I., Mashrur, F.R., Rahman, K.M., Vaidyanathan, R., Anwar, S.F., Sarker, F., Ali, N.A., Tat, H.H. and Mamun, K.A. (2025) ‘Machine learning-based viewers’ preference prediction on social awareness advertisements using EEG’, Frontiers in Human Neuroscience, 19, 1542574.
24. Kakaria, S., Saffari, F., Ramsøy, T.Z. and Bigné, E. (2023) ‘Cognitive load during planned and unplanned virtual shopping: Evidence from a neurophysiological perspective’, International Journal of Information Management, 72, 102667.
25. Khan, Anwar , Naquvi ,Kamran Javed, Haider, Md Faheem and Khan, Mohsin Ali . (2024) ‘Quality by design-newer technique for pharmaceutical product development’, Intelligent Pharmacy, 2(1), pp. 122–129. Available at: https://doi.org/10.1016/j.ipha.2023.10.004
26. Kryzanowski, L. and Rouhghalandari, A. (2024) ‘Institutional/retail investor active attention and behavior: Firm coverage on Mad Money’, Journal of Behavioral and Experimental Finance, 42, 100937.
27. Landmann, E. (2023) ‘I can see how you feel: Methodological considerations and handling of FaceReader software for emotion measurement’, Technological Forecasting and Social Change, 197, 122889.
28. Li, S., Chark, R., Bastiaansen, M. and Wood, E. (2023) ‘A review of research into neuroscience in tourism’, Annals of Tourism Research, 101, 103615.
29. Li, S., Lyu, T., Park, S. and Choi, Y. (2023) ‘Spillover effects in destination advertising: An electroencephalography study’, Annals of Tourism Research, 102, 103623.
30. Lin, M.H., Jones, W. and Childers, T.L. (2024) ‘Neuromarketing as a scale validation tool: Understanding individual differences based on the style of processing scale in affective judgements’, Journal of Consumer Behaviour, 23, pp. 171–185.
31. Liu, Y., Zhao, R., Xiong, X. and Ren, X. (2023) ‘A bibliometric analysis of consumer neuroscience towards sustainable consumption’, Behavioral Sciences, 13, 298.

32. Lopez-Navarro, R., Montero-Vicente, L., Escriba-Perez, C. and Buitrago-Vera, J.M. (2025) 'Implicit and explicit consumer perceptions of cashews: A neuroscientific and sensory analysis approach', Foods, 14, 1213.
33. Lyulyov, O., Pimonenko, T., Infante-Moro, A. and Kwilinski, A. (2024) 'Perception of artificial intelligence: GSR analysis and face detection', Virtual Economics, 7, pp. 7–30.
34. Marques dos Santos, J.P. and Marques dos Santos, J.D. (2024) 'Explainable artificial intelligence in neuromarketing/consumer neuroscience: An fMRI study on brand perception', Frontiers in Human Neuroscience, 18, 1305164.
35. Marques, J.A.L., Neto, A.C., Silva, S.C. and Bigné, E. (2025) 'Predicting consumer ad preferences: Leveraging a machine learning approach for EDA and FEA neurophysiological metrics', Psychology & Marketing, 42, pp. 175–192.
36. Mashrur, F.R., Rahman, K.M., Miya, M.T.I. and Vaidyanathan, R. (2024) 'Intelligent neuromarketing framework for consumers' preference prediction from electroencephalography signals and eye tracking', Journal of Consumer Behaviour.
37. McInnes, A.N. and Sung, B. (2024) 'A neglected consumer neuroscience technique: Pupillometry and its practical application to consumer research', International Journal of Research in Marketing.
38. McInnes, A.N., Sung, B. and Hooshmand, R. (2023) 'A practical review of electroencephalography's value to consumer research', International Journal of Market Research, 65, pp. 52–82.
39. Nair, P.S. and Shiva, A. (2023) 'Do social media interaction drive behavioral bias and trading tendencies of retail investors? A moderated-mediation approach', Journal of Content, Community and Communication, 17, pp. 143–154.
40. Pšurný, M., Mokrý, S. and Stavkova, J. (2024) 'Exploring consumers' perceptions of online purchase decision factors: Electroencephalography and eye-tracking evidence', Frontiers in Human Neuroscience.
41. Sharma, D.J. and Sarma, N.N. (2024) 'Impact of behavioral biases on fundamental analysis factors of investment decision: A study on retail investors in Assam', IUP Journal of Applied Finance.
42. Sharma, S. and Negi, V. (2025) 'Effect of behavioural biases on investors' decision making: A systematic literature review', Metamorphosis, pp. 105–113.
43. Singh, H. and Chaudhary, A.K. (2024) 'Behavioral attributes influencing decision making of Indian derivative market investors', Asian Journal of Economics, Business and Accounting, 24(6), pp. 464–476.
44. Singh, S., Bharti, I. and Maurya, P. (2025) 'A comprehensive review of prominent biases and other factors influencing retail investors' decision-making', Indian Journal of Finance, 19(7).
45. Šola, H.M., Qureshi, F.H. and Khawaja, S. (2024) 'AI-powered eye tracking for bias detection in online course reviews: A Udemy case study', Big Data and Cognitive Computing, 8, 144.
46. Šola, H.M., Qureshi, F.H. and Khawaja, S. (2025) 'Human-centred design meets AI-driven algorithms: Comparative analysis of political campaign branding', Informatics, 12, 30.
47. Tan, W. and Lee, E.J. (2024) 'Neuroimaging insights into breaches of consumer privacy: Unveiling implicit brain mechanisms', Journal of Business Research, 182, 114815.
48. Ülker, S.V., Sümer, B.N., Sönmez Kence, E. and Hizli Sayar, F.G. (2025) 'Psychophysiological investigation of the effects of virtual reality, the new dimension of retail shopping, on Generation Z', International Journal of Human-Computer Interaction, 41, pp. 3926–3939.
49. Wang, J., Alsharif, A.H., Abd Aziz, N., Khraiwish, A. and Salleh, N.Z.M. (2024) 'Neuro-insights in marketing research: A PRISMA-based analysis of EEG studies on consumer behavior', SAGE Open, 14.
50. Yüksel, D. (2023) 'Investigation of web-based eye-tracking system performance under different lighting conditions for neuromarketing', Journal of Theoretical and Applied Electronic Commerce Research, 18, pp. 2092–2106.
51. Zahmati, M., Azimzadeh, S.M., Sotoodeh, M.S. and Asgari, O. (2023) 'An eye-tracking study on how the popularity and gender of endorsers affected the audience's attention on the advertisement', Electronic Commerce Research, 23, pp. 1665–1676.