International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
Volume 4, Issue 5, Sep-Oct-2026, PP: 01-12
ISSN:3048-7722

Designed to Trade? Product Design, Choice Architecture and Retail Trading Frequency on Indian Discount-Broking Platforms

Palash Jauhari
MBA Candidate, SVKM's NMIMS School of Business Management, Mumbai, India

***Abstract* – Discount-broking applications have transformed retail access to Indian capital markets. Zero brokerage on equity delivery, paperless onboarding and one-tap order execution have removed long-standing financial and operational barriers. At the same time, regulatory studies show that more than nine in ten individual traders in equity futures and options (F&O) lose money. This paper asks whether, and through which channels, the design of a trading application shapes how often and how speculatively its users trade. We make three contributions. First, we develop a conceptual framework that links six product-design levers (visual salience of profit-and-loss and top movers, gamification, order friction, push notifications, derivatives prominence and voluntary friction tools such as a kill switch) to behavioural mediators (attention, fear of missing out, overconfidence, myopic loss aversion and loss-chasing) and to measurable investor outcomes. Second, we set out a mixed-methods empirical design (a platform design audit, a survey, a randomised interface experiment and interviews) together with its econometric specification. Third, we build and run an agent-based model of 5,000 heterogeneous investors, simulated over 30 Monte Carlo replications, and use it to test the internal logic of the framework and the identification strategy. Under our stated assumptions, an engagement-first design generates about 4.1 times as many orders per month as a utility-first design (6.6 vs. 1.6), a higher F&O share of orders (32.0% vs. 12.1%), shorter holding periods (26.8 vs. 43.6 days) and far higher derivatives adoption among novices (50.4% vs. 13.6%). A voluntary kill switch reduces F&O orders by only 5.6%, whereas a mandatory cooling-off step reduces them by 40.7%. Because these results come from a calibrated simulation rather than observed trading data, we present them as quantified hypotheses and as a validated research design, not as empirical estimates. We close with implications for ethical product management in fintech and for the Securities and Exchange Board of India (SEBI).**

***Keywords* – Behavioural finance; choice architecture; digital engagement practices; dis-count brokers; retail investors; F&O trading; gamification; agent-based modelling; product management.**

I. Introduction

India's retail investor base has grown faster in the last five years than at any point in its history, and most of that growth has come through mobile-first discount brokers. These firms compete on price, since equity delivery trades are typically free of brokerage, and above all on experience: account opening takes minutes, order tickets need a few taps, and the home screen shows live prices, top gainers and a real-time profit-and-loss (P&L) figure. By October 2023, a newer mass-market platform, Groww, had overtaken the long-time market leader, Zerodha, in active clients on the National Stock Exchange (Business Standard, 2023). The competition for retail attention is therefore, to a large extent, a competition in product design.

The social stakes are high. SEBI's own studies of the equity derivatives segment show persistent, concentrated losses among individuals. Over FY22–FY24, 93% of more than one crore individual F&O traders incurred losses, averaging about Rs 2 lakh per trader including transaction costs. Aggregate losses exceeded Rs 1.8 lakh crore, and more than 75% of loss-making traders kept trading (Securities and Exchange Board of India, 2024b). In FY25, 91% of individual traders lost money, and net losses rose by 41% to about Rs 1.06 lakh crore (Securities and Exchange Board of India, 2025). The same studies report a rising share of traders below the age of 30 (43% in FY24) and a majority from beyond India's top 30 cities. These are exactly the groups most likely to have entered the market through an app.

SEBI's regulatory response has so far worked on the product side of derivatives: larger contract sizes, fewer weekly expiries, upfront premium collection and tighter margins (Securities and Exchange Board of India, 2024a). It has not yet addressed the interface through which retail investors meet those products. Regulators elsewhere have started to ask this question. In 2021 the U.S. Securities and Exchange Commission sought public comment on "digital engagement practices" such as gamification, behavioural prompts and push notifications (U.S. Securities and Exchange Commission, 2021). The academic literature offers strong evidence that attention and interface design move retail trading (Barber et al., 2022; Liao et al., 2021; Chapkovski et al., 2026), but almost none of it concerns India, and very little of it breaks "design" into specific levers that a product manager can actually change.

This paper addresses that gap. It asks:

RQ1. How does the intensity of app engagement relate to the monthly trading frequency of retail investors in India?

RQ2. How do platform-specific design choices (salience, gamification, derivatives promi-nence) change the mix between delivery equity and F&O?

International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
Volume 4, Issue 5, Sep-Oct-2026, PP: 01-12
ISSN:3048-7722

RQ3. Do voluntary friction tools such as a kill switch reduce overtrading after losses and during volatile markets?

We make three contributions.

- A lever-level conceptual framework. We break “platform design” into six measurable levers and link each to a behavioural mechanism grounded in established theory, with a testable prediction for each (Section 4).
- An implementable empirical design. We propose a design-audit rubric that turns real applications into numeric design scores, a four-stage mixed-methods programme, and a matching set of econometric specifications for panel, mediation, adoption and difference-in-differences analysis (Section 5).
- A working agent-based model. We implement the framework as an agent-based simula-tion. We use it to (i) derive quantitative, falsifiable predictions, (ii) rank the design levers by their effect, (iii) compare interventions such as a kill switch and a cooling-off step, and (iv) check that the proposed econometric methods recover known effects from data with realistic confounding (Section 6).

We are deliberate about what the simulation can and cannot show. Its outputs follow from assumed behavioural parameters. They show what the framework implies, how large the effects could be, and whether the empirical strategy would detect them. They do not show that any particular platform causes any particular behaviour. We therefore present the two archetypes in the simulation as stylised design philosophies and not as descriptions of any named firm. Section 8 discusses these limits in detail.

The rest of the paper is organised as follows. Section 2 describes the institutional setting. Section 3 reviews the literature. Section 4 develops the conceptual framework and hypotheses. Section 5 sets out the empirical design and the simulation model. Section 6 reports the simulation results. Section 7 discusses implications for product management and regulation, Section 8 sets out the limitations, and Section 9 concludes.

II. INSTITUTIONAL BACKGROUND

The discount-broking model in India

Traditional full-service brokers charged a percentage of turnover and relied on relationship managers, phone orders and research products. Discount brokers replaced this with a flat per-order fee on intraday and F&O trades and, for most platforms, zero brokerage on equity delivery. Revenue therefore depends heavily on order count in the fee-bearing segments, on float income and on ancillary products. This matters for our argument: when revenue grows with the number of orders, the firm has a commercial incentive to design for engagement and order velocity. That incentive is not always aligned with the long-run returns of the customer, especially in derivatives.

Heterogeneity in design philosophy

Indian platforms differ visibly in how they handle this tension. Some have chosen a dense, analytical interface and have added tools that deliberately add friction. The clearest example is Zerodha’s “kill switch”, introduced in June 2021, which lets a trader disable one or more segments. Once disabled, a segment cannot be re-enabled for 12 hours. The firm justified the feature by arguing that “over-trading is the biggest destroyer of capital” (Zerodha, 2021). Other platforms have prioritised simplicity and discovery, with asset-first home screens, curated lists of trending stocks and short paths from browsing to buying. Neither approach is inherently good or bad. Simplicity lowers barriers for first-time investors, which is a real benefit. The question this paper asks is how each lever affects trading behaviour, and in which direction.

Regulatory context

SEBI’s October 2024 circular on equity index derivatives raised minimum contract values to Rs 15–20 lakh, limited weekly expiries to one benchmark index per exchange, required upfront collection of option premiums, removed calendar-spread benefits on expiry day, added an extra 2% extreme-loss margin on short options on expiry day, and introduced intraday monitoring of position limits (Securities and Exchange Board of India, 2024a). The measures act on contract design and margins. None of them acts on interface design, notification practices or in-app defaults, which is the regulatory space this paper examines.

III. LITERATURE REVIEW

Overtrading and overconfidence

A large body of evidence shows that individual investors trade too much and that the most active traders earn the lowest net returns. Odean (1999) finds that the stocks investors buy underperform the stocks they sell, even before costs. Barber and Odean (2000) show that the most active fifth of U.S. brokerage households earn substantially lower net returns than the least active. Overconfidence is the leading explanation: investors overestimate the precision of their information (Barber and Odean, 2001), and early success can make them more confident than their skill justifies (Gervais and Odean, 2001). Grinblatt and Keloharju (2009) link trading activity in Finland to both overconfidence and sensation seeking. That second trait is directly relevant to interfaces built around novelty, motion and reward.

Attention and salience

Investors cannot process every security, so they buy what grabs their attention (Barber and Odean, 2008). In the app era, the interface decides what is attention-grabbing. Barber et al. (2022) show that Robinhood users concentrated their purchases in stocks on the app’s “Top Movers” list, and that these attention-driven purchases were followed by negative returns. Welch (2022) gives a more positive view of the aggregate Robinhood portfolio, and Eaton et al. (2022) show that platform outages, which temporarily remove app-based retail traders, affect market quality. Together these

International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
Volume 4, Issue 5, Sep-Oct-2026, PP: 01-12
ISSN:3048-7722

studies establish that app design is a first-order influence on retail order flow.

Myopic loss aversion and monitoring frequency

Prospect theory holds that losses weigh more heavily than equal gains (Kahneman and Tversky, 1979). Benartzi and Thaler (1995) show that when investors evaluate portfolios frequently, loss aversion makes risky assets look less attractive and invites reactive behaviour. Experimental evidence confirms that more frequent feedback reduces risk-taking in long-horizon investments and increases reactivity (Thaler et al., 1997). A real-time P&L figure on the home screen is, in effect, the most frequent evaluation period possible.

Choice architecture, habit formation and dark patterns

The way choices are presented changes the choices people make (Thaler and Sunstein, 2008). Defaults, ordering and friction are powerful even when every option remains available. Habit-forming products follow a cycle of trigger, action, variable reward and investment (Eyal, 2014). That cycle builds on the finding that variable-ratio reinforcement produces persistent, extinction-resistant behaviour (Ferster and Skinner, 1957). Human–computer interaction research has documented "dark patterns" across digital commerce, meaning interface choices that steer users toward outcomes that benefit the firm (Mathur et al., 2019).

Technology, interfaces and trading

Evidence that the channel itself changes behaviour predates smartphones. Barber and Odean (2002) find that investors who moved to online trading traded more actively and performed worse. Kalda et al. (2021) compare the same investors across devices and show that smartphone use is associated with riskier, more attention-driven purchases. Using Chinese brokerage data, Liao et al. (2021) show that changing what a brokerage interface displays about investors' own gains and losses alters their trading decisions. Most directly, Chapkovski et al. (2026) show experimentally that gamified trading environments increase trading activity.

Research gap

Three gaps motivate this paper. First, almost no published research examines Indian discount-broking platforms, even though India has one of the world's largest retail derivatives markets and some of the best-documented retail losses. Second, most studies treat "the app" as a single treatment. Few break it into levers such as salience, friction, notifications and derivatives prominence, which are the variables that product managers and regulators can actually change. Third, there is little work on counter-design, meaning friction tools such as kill switches or cooling-off periods, and on whether voluntary tools are enough. The framework and model below are built to address all three.

IV. CONCEPTUAL FRAMEWORK AND HYPOTHESES

From interface to outcome

Figure 1 shows the framework. Design levers operate on investors through behavioural mediators, and investor traits moderate the effect. The resulting outcomes, especially P&L, feed back into the mediators. Losses trigger loss-chasing and more frequent checking, which is how a design effect can compound over time. Regulation acts on the design layer.

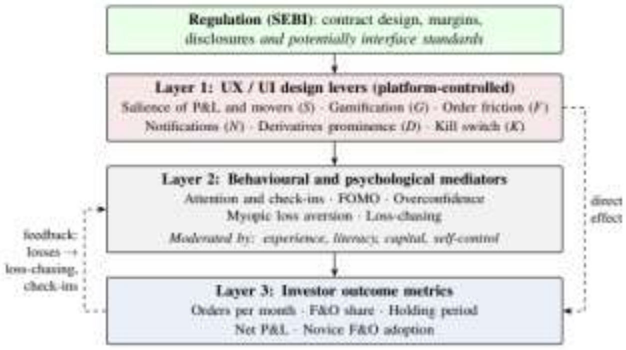

Figure 1: Conceptual framework. Solid arrows show the hypothesised causal path; dashed arrows show the direct effect of design that does not pass through measured attention (right) and the P&L feedback loop (left).

Design levers and mechanisms

Table 1 links each lever to a concrete interface feature, a mechanism, a theory and a predicted effect. The table turns the framework into claims that can be tested.

The habit loop in a trading app

Figure 2 places these levers in the habit-formation cycle. A push alert or a sharp price move is the trigger. A one-tap order is the low-effort action. The instantly updating P&L is a variable reward: sometimes green, sometimes red, and never predictable. Watchlists, activated F&O

Table 1: Design levers, behavioural mechanisms and predicted effects

Lever	Interface example	Mechanism	Theory	Predicted effect
Salience (*S*)	Live, colour-coded P&L on the home screen; "top gainers" lists	Attention capture; frequent evaluation	Barber and Odean (2008); Benartzi and Thaler (1995)	More sessions and orders; more speculative mix
Gamification	Execution	Variable-ratio	Ferster and	Shorter holding
(*G*)	animations, sounds, badges, streaks	reward; sensation seeking	Skinner (1957); Grinblatt and Keloharju (2009)	periods; habit loop
Friction (*F*)	Number of taps and confirmations per order; biometric one-tap	Removes cooling-off time	Thaler and Sunstein (2008)	Fewer impulsive orders as *F* rises

International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
Volume 4, Issue 5, Sep-Oct-2026, PP: 01-12
ISSN:3048-7722

Notifications (N)	Price alerts, "stock is moving" pushes	External trigger	Eyal (2014)	More sessions, hence more orders
Derivatives	Option chain on	Default and salience	Thaler and	Higher F&O
prominence (D)	home or search; F&O one tap away	of risky product	Sunstein (2008)	adoption and share
Friction tools (K)	Kill switch; segment lock	Commitment device	Thaler and Sunstein (2008)	Less post-loss trading, if used

segments and streaks are the investment that brings the user back. The same loop that makes an app "sticky" can make trading compulsive.

Hypotheses

Building on the framework, we state five hypotheses. H1–H3 come from the original research blueprint. H4 and H5 make the mediation and friction-tool claims explicit.

H1 (Salience).

Higher visual salience of daily gainers and losers and of real-time mark-to-market P&L is positively associated with trading frequency and with the share of speculative (F&O) turnover.

H2 (Gamification).

Gamified design elements (execution animations, celebratory sounds, trend badges) reduce investors' average holding period.

H3 (Friction and novices).

Platforms with higher order and activation friction show lower rates of options-trading

|}

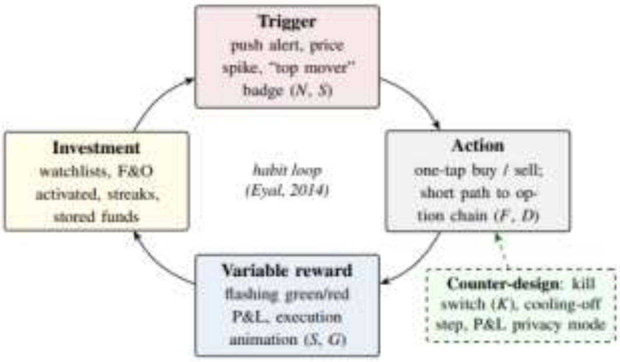

Figure 2: The trigger–action–reward–investment loop mapped onto a trading app, and where counter-design tools interrupt it.

adoption among novice investors (less than one year of experience).

H4 (Mediation).

Part of the effect of salience and notifications on trading frequency is transmitted through app engagement (sessions and time spent).

H5 (Friction tools).

Availability of a kill switch reduces F&O trading on days after large losses. The effect depends on take-up, so a default-on or mandatory mechanism is stronger than an opt-in tool.

V. METHODOLOGY

The methodology has two parts. Section 5.1 sets out the empirical programme that would test the hypotheses on real investors. Section 5.2 describes the agent-based model we built and ran for this paper. The model serves as a pre-registration device: it produces quantified predictions and a dry run of the planned statistical tests.

Proposed empirical programme

Four-stage mixed-methods design

Figure 3 summarises the programme. We have added a design audit stage to the original three-stage blueprint. Without it, "design" cannot enter a regression as a number.

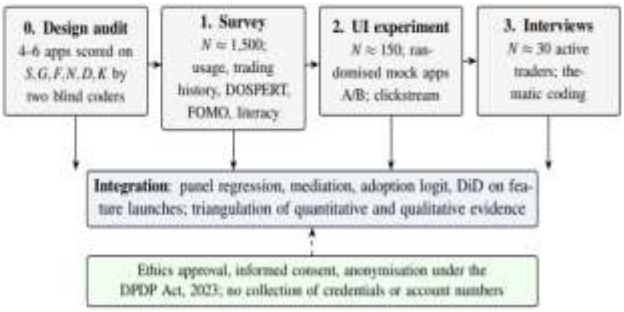

Figure 3: Proposed mixed-methods research pipeline.

Stage 0: Design audit. Two coders, blind to the hypotheses, complete a fixed set of tasks on each app, such as "buy one share of a Nifty-50 stock" and "reach the Nifty option chain from the home screen". They score each app using the rubric in Table 2. Inter-rater reliability is reported, for example using Cohen's κ.

Table 2: Design-audit rubric for scoring real applications

Lever	Operational measure	Scale
Salience S	Share of home-screen area showing live P&L or movers; colour intensity; animation of price changes	0–1 composite
Gamification G	Count of reward cues (animation, sound, badge, confetti, streak) across 10 standard tasks	0–1 (normalised)
Friction F	Taps and confirmations from home screen to executed market order	Count (1–8)
Notifications N	Default push notifications per day in a two-week test account	Count per day
Derivatives prominence D	Taps from home screen to option chain; F&O visible on home or search by default	0–1 composite
Friction tools K	Kill switch, segment lock, loss limits, P&L privacy mode available	0/1 each

Stage 1: Survey. A stratified sample of about 1,500 active retail investors across Tier-1, Tier-2 and Tier-3 cities, recruited through investor communities and universities. The survey collects: self-reported and, where participants consent, screenshot-verified usage (screen time, daily

sessions); trading history (orders per month, segment mix, holding period); and validated scales for risk-taking (DOSPERT; Weber et al., 2002), fear of missing out (Przybylski et al., 2013) and financial literacy (Lusardi and Mitchell, 2014).

Stage 2: Randomised interface experiment. About 150 participants trade in a simulated market using one of two mock applications that are identical except for the design levers. The engagement-first variant has high S, G and D and low F. The utility-first variant is the reverse and includes a kill switch. Because participants are randomly assigned, this stage identifies causal effects of design that the survey cannot. The outcomes are clickstream data, time to trade, order counts and segment choice.

Stage 3: Interviews. About 30 semi-structured interviews with active traders, coded themat-ically (for example in NVivo), to capture emotional triggers, such as “I saw it moving on the home screen”, and self-control strategies.

Identification challenges

The central threat to causal inference in observational data is self-selection. Investors who want to trade actively may choose engagement-first platforms. Figure 4 makes this explicit. Traits such as overconfidence affect both platform choice and trading, so a naive cross-platform comparison overstates the design effect. Our design addresses this in three ways: (i) randomisation in Stage 2; (ii) controls for measured traits in Stage 1; and (iii) within-platform feature launches, such as the introduction of a kill switch, which can be analysed as natural experiments using difference-in-differences (Angrist and Pischke, 2009).

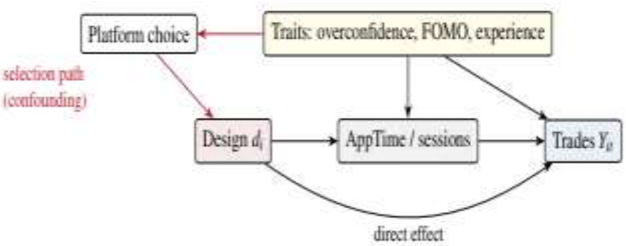

Figure 4: Causal diagram. Investor traits confound the design–trading relationship through platform choice (red path). Randomisation, trait controls and within-platform feature changes block this path.

Econometric specification

The main specification is a panel model of trading intensity for investor i in month t:

$Y_{it} = \beta_0 + \beta_1 \, AppTime_{it} + \beta_2 S_i + \beta_3 F_i + \delta' d_i + \gamma' X_{it} + \tau_t + \varepsilon_{it}$, (1)

where Y_{it} is ln(1 + $orders_{it}$) (with Poisson count models as a robustness check), $AppTime_{it}$ is average daily minutes on the app, S_i and F_i are the salience and friction scores from the audit, d_i contains the remaining design levers (G, N, D, K), X_{it} contains controls (capital, experience, FOMO and overconfidence scales), and τ_t are month fixed effects that absorb market-wide volatility. Standard errors are clustered by investor.

Because AppTime is itself an outcome of design (Figure 4), Equation (1) estimates the direct effect of design. H4 is tested by comparing it with the total effect from the same model without AppTime (Baron and Kenny, 1986):

$$\text{Mediated share}_S = \frac{\beta_2^{\text{total}} - \beta_2^{\text{direct}}}{\beta_2^{\text{total}}}.$$

H3 is tested with a logit model of F&O activation among novices, $\Pr(Adopt_i = 1) = \Lambda(\alpha + \varphi F_i + \psi D_i + \gamma' X_i)$. H5 is tested with a two-way fixed-effects difference-in-differences model around the introduction of a kill switch:

$FO_{it} = \mu_i + \tau_t + \theta\,(Treat_i \times Post_t) + \varepsilon_{it}$. (3)

Agent-based simulation model

Why simulate?

Agent-based models represent heterogeneous individuals who follow simple behavioural rules. They are well suited to systems in which feedback loops make aggregate outcomes hard to derive analytically (Bonabeau, 2002). We use the model for four purposes: to turn the framework into quantitative predictions; to rank the design levers; to compare policy interventions that have not yet been tried; and to test whether the econometric design in Section 5.1 can recover effects that we know are present because we built them into the model.

Model structure

The model simulates a population of investors over 252 trading days (12 months of 21 days). Figure 5 shows the daily sequence. The Python source code and the script that reproduces every table and figure in this paper are provided with the paper (Appendix C).

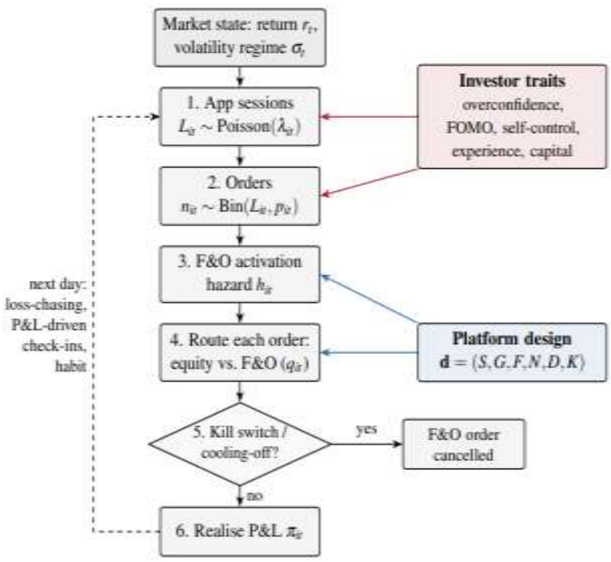

Figure 5: Daily sequence of the agent-based model. Blue arrows show design inputs; red arrows show investor traits; the dashed loop is the P&L and habit feedback.

Investors. Each investor i has a trading capital Wi (log-normal, median Rs 1.5 lakh), trading experience (log-normal; investors with less than one year are novices), and three standardised traits: overconfidence OCi, fear of missing out FOMOi, and self-control SCi.

Market. Daily returns are rt ∼ N (μ, σ 2). Volatility σt switches between a normal and a high regime (2.2 times normal) following a two-state Markov chain. The salience of today's move is mt = |rt|/σ¯ .

1. Attention. **App** sessions follow a Poisson process whose intensity rises with notifications, salience (amplified by FOMO), volatility, habit and yesterday's P&L:

$$\ln \lambda_{it} = \theta_0 + \theta_N \ln(1+N) + \theta_S S(1+0.3\,FOMO_i) + \theta_V \left(\frac{\sigma_t}{\bar{\sigma}} - 1\right) + \theta_H (1+G)\ln(1+L_{i,t-1}) + \theta_P \min\left(\frac{100|\pi_{i,t-1}|}{W_i}, 5\right).$$

(4)

The habit term θH(1 + G) ln(1 + Li,t−1) is how the model represents variable-ratio reinforcement: yesterday's sessions raise today's, and gamification strengthens this persistence.

2. Orders. In each session the investor places an order with probability

pit = Λ(α0 + αSS + αGG − αF (F − 1) + αOCOCi + αMFOMO+mt + αRRit), (5)

where Λ is the logistic function and Rit = 1 if yesterday's loss exceeded 1% of capital (loss-chasing, or "revenge trading").

4. Derivatives. Investors who have not yet activated F&O do so with daily hazard hit = Λ(β0 + βDD − βF (F − 1) + βOCOCi + βMmt). For activated investors, each order goes to F&O with probability qit = Λ(γ0 + γDD + γOCOCi + γMmt + γRRit).

5. Friction tools. If a kill switch is available (K = 1) and yesterday's loss exceeded 2% of capital, the investor switches off the F&O segment with probability Λ(κ0 + κSCSCi), which blocks F&O orders that day. At the baseline κ0 = −1.5, this take-up probability is about 18% for an investor of average self-control. In the cooling-off counterfactual, every F&O order passes through a mandatory confirmation step. Impulsive orders are abandoned with probability ρ Λ(−1 + 0.4 FOMO+mt + Rit), and activating the F&O segment requires two additional steps.

6. Returns. A delivery-equity order of size x = Wi · U (0.03, 0.10) is held for h days and earns
x(μeh + σe√hz − ce), where

$$h \sim \mathrm{Exp}\left(H_0\, e^{-k_1 G - k_2 \ln(1+L_{it})}\right), \qquad h \geq 1.$$

(6)

Frequent check-ins and gamification therefore shorten holding periods; this is our representation of myopic loss aversion. An F&O order (modelled as option buying, the dominant retail strategy) has a premium outlay of y = Wi · U (0.01, 0.04), scaled up with overconfidence and by a factor of 1.5 after a loss. It returns a log-normal gain with probability 0.33 and a loss of 40–100% of the premium otherwise. The expected gross return is about −16% of the premium, before variable costs of 1.2% and a fixed cost of Rs 40 per round trip.

Archetypes and parameters

Table 3 defines the two design archetypes. They are stylised. Archetype B includes a kill switch, a feature that exists in the Indian market (Zerodha, 2021). Apart from that feature, neither archetype is a coded measurement of any real application. Mapping real apps onto the design space requires the audit in Table 2. Table 4 lists the behavioural parameters. These are assumptions, chosen so that simulated activity and loss rates fall in plausible ranges. They are not estimates, and Section 6.7 examines how the conclusions change when they are varied.

Table 3: Stylised design archetypes used in the simulation

Archetype	*S*	*G*	*F*	*N*	*D*	*K*	**Design philosophy**
A: engagement-first	0.9	0.8	3	4	0.8	0	Discovery-led, low friction, rich feedback
B: utility-first	0.3	0.1	6	1	0.3	1	Analytical, neutral visuals, friction tools

Experimental protocol

Table 4: Behavioural parameters of the agent-based model (baseline values)

Block	**Parameters**	**Interpretation**
Attention	$\theta_0 = -0.45$, $\theta_N = 0.30$, $\theta_S = 0.40$, $\theta_V = 0.25$, $\theta_H = 0.12$, $\theta_P = 0.05$	Sessions rise with alerts, salience, volatility, habit and P&L swings
Order decision	$\alpha_0 = -2.3$, $\alpha_S = 0.40$, $\alpha_G = 0.35$, $\alpha_F = 0.10$, $\alpha_{OC} = 0.40$, $\alpha_M = 0.15$, $\alpha_R = 0.60$	Each extra step of friction lowers the log-odds of an order by 0.10
F&O activation	$\beta_0 = -7.0$, $\beta_D = 1.8$, $\beta_F = 0.25$, $\beta_{OC} = 0.50$, $\beta_M = 0.15$	One-time hazard; 25% of experienced investors start activated
F&O routing	$\gamma_0 = -0.6$, $\gamma_D = 1.2$, $\gamma_{OC} = 0.4$, $\gamma_M = 0.1$, $\gamma_R = 0.5$	Prominence and loss-chasing tilt orders toward F&O
Holding period	$H_0 = 60$, $k_1 = 0.60$, $k_2 = 0.25$	Gamification and frequent checks shorten holding
Kill switch	trigger 2% loss; $\kappa_0 = -1.5$, $\kappa_{SC} = 1.0$	Voluntary; take-up rises with self-control
Cooling-off	$\rho = 0.6$; +2 activation steps	Share of impulsive F&O orders abandoned
Market	$\bar{\sigma} = 1.1\%$; high regime 2.2×; entry 3%, persistence 80%	About 13% of days are high-volatility

The baseline comparison uses a paired design. For each of 30 Monte Carlo replications, the same simulated population of 5,000 investors faces the same market path under each archetype, so differences are due to design alone. That gives 300,000 investor-years in total. Design sweeps, lever decompositions and policy scenarios use 5 replications per

International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
Volume 4, Issue 5, Sep-Oct-2026, PP: 01-12
ISSN:3048-7722

setting. The econometric check uses a separate population of 6,000 investors, each assigned a random design vector, which yields a panel of 72,000 investor-months. Trait scales in this panel are measured with noise (reliability about 0.8) to mimic survey error.

VI. SIMULATION RESULTS

Reading guide. All results in this section come from the model. Where a result follows directly from an assumption, we say so. The results that matter most are the emergent ones: magnitudes, rankings and interactions that no single assumption fixes.

Baseline: engagement-first versus utility-first design
Table 5 and Figure 6 compare the archetypes. Investors on the engagement-first design open the app about 41.2 times a month, against 21.1 on the utility-first design. They place 6.6 orders a month against 1.6, about 311% more. The difference is larger than the difference in sessions because design raises both the number of sessions and the chance of ordering in each session. F&O accounts for 32.0% of orders under A and 12.1% under B. Delivery holdings last 26.8 days on average under A against 43.6 under B. Half the novices (50.4%) activate derivatives within a year under A, compared with 13.6% under B.

The welfare implications follow. Among investors who trade F&O, 87.7% lose money on derivatives over the year under A, against 75.5% under B. The mean F&O loss per F&O user is about Rs 83.2 thousand under A and Rs 15.4 thousand under B. The median investor's net

Table 5: Baseline outcomes by design archetype (30 paired Monte Carlo replications)

Outcome (per investor)	**A**	**B**	**A − B**	**95% MC interval**
App sessions per investor-month	41.2	21.1	20.2	[19.4, 21.2]
Orders per investor-month	6.58	1.60	4.98	[4.73, 5.29]
F&O share of orders (%)	32.0	12.1	19.9	[18.9, 21.0]
F&O share of turnover (%)	20.6	6.3	14.3	[13.1, 15.5]
Mean delivery holding period (days)	26.8	43.6	-16.8	[-17.1, -16.5]
Novices activating F&O in year (%)	50.4	13.6	36.9	[34.3, 39.8]
F&O users with net F&O loss (%)	87.7	75.5	12.1	[10.3, 14.3]
Mean F&O loss per F&O user (INR ’000)	83.2	15.4	67.8	[59.2, 80.4]
Median net annual return on capital (%)	-2.45	0.88	-3.34	[-3.92, -2.94]

Notes: A = engagement-first, B = utility-first (Table 3). Values are means across replications; the interval is the 2.5th–97.5th percentile of the paired difference across replications. F&O loss statistics are computed over investors who placed at least one F&O order in the year.

Archetype A (engagement-first) vs B (utility-first); bars = mean of 30 runs, whiskers = 95% Monte Carlo range

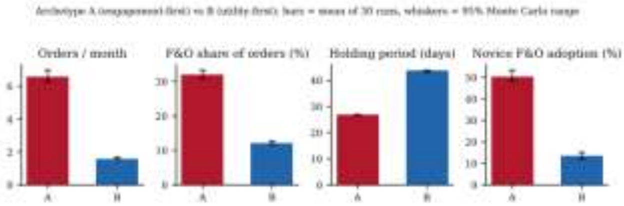

Figure 6: Key outcomes by design archetype. Bars show means over 30 replications; whiskers show the 95% Monte Carlo range.

annual return on capital is -2.45% under A and 0.88% under B. The loss rate under A is close to the 91–93% that SEBI reports for individual F&O traders (Securities and Exchange Board of India, 2024b, 2025). This is a useful plausibility check, but it is not a validation, because loss rates were one of the targets used in choosing the parameters.

Design sweeps: testing H1–H3
Figure 7 varies one lever at a time, starting from Archetype

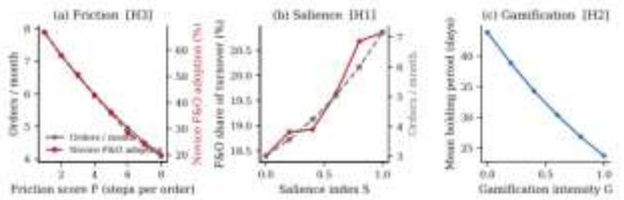

Figure 7: One-at-a-time design sweeps from Archetype A (5 replications per point). (a) Friction lowers order frequency and, more steeply, novice F&O adoption. (b) Salience raises order frequency and the F&O share of turnover. (c) Gamification shortens holding periods.

H1 (salience). Raising salience from 0 to 1 more than doubles order frequency, from 3.0 to 7.2 orders a month, and raises the F&O share of turnover from 18.4% to 20.9%. The effect on the mix is much weaker than the effect on volume. In the model, salience mainly increases how much people trade and only secondarily what they trade, because the routing decision depends on derivatives prominence rather than on salience. An empirical test should therefore measure turnover and segment mix separately.

H2 (gamification). Moving gamification from 0 to 1 shortens the mean delivery holding period from 43.9 to 23.7 days. This works through two channels: the direct assumption (k1) and the indirect effect of more frequent sessions (k2), which gamification increases through the habit term.

H3 (friction and novices). Each additional step between the home screen and an executed order lowers novice F&O adoption by about 6.8 percentage points, from 66.8% with one-tap execution to 19.6% with eight steps. Friction matters more for the one-time entry decision into derivatives than for routine trading, because a decision

ISSN:3048-7722
International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
Volume 4, Issue 5, Sep-Oct-2026, PP: 01-12

taken once can be blocked once, while routine orders face friction every time but only lose a little each time.

Which levers matter most? A decomposition

Product managers and regulators need to know which levers matter most. Table 6 and Figure 8 start from Archetype A and switch one lever at a time to its Archetype B value.

Table 6: Lever decomposition: effect of switching one lever from A to B Lever Change (A → B) Δ all orders (%) Δ F&O orders (%)

Lever	Change (A → B)	Δ all orders (%)	Δ F&O orders (%)
Derivatives prominence	0.8 → 0.3	-2.4	-47.4
Order friction	3 → 6	-24.3	-46.4
Salience of P&L / movers	0.9 → 0.3	-40.6	-43.1
Push notifications	4 → 1	-28.7	-30.7
Gamification	0.8 → 0.1	-26.9	-28.4
Kill switch	0 → 1	-1.7	-5.6

Notes: Changes relative to Archetype A; 5 replications per row; sorted by effect on F&O orders.

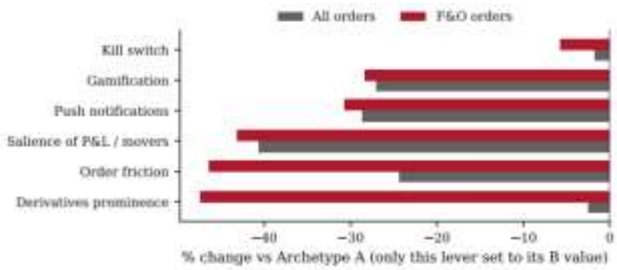

Figure 8: Lever decomposition. Salience and notifications move total activity; derivatives prominence and friction move derivatives activity.

Three patterns stand out. First, the levers split into volume levers and mix levers. Salience (-40.6%), notifications (-28.7%) and gamification (-26.9%) reduce total orders substantially, and they reduce F&O orders by roughly the same proportion, so the mix barely changes. Derivatives prominence is the opposite: it barely changes total orders (-2.4%) but cuts F&O orders by -47.4%. Second, order friction acts on both volume and mix. It reduces total orders by -24.3%, and F&O orders by almost twice as much (-46.4%), because it raises the cost of both routines ordering and the one-time activation decision. Third, the voluntary kill switch has the smallest effect (-5.6% on F&O orders). The reason is not that it fails when used. It is that, at the assumed take-up, it is used too rarely. None of the single-lever effects comes close to the full A-to-B gap, which shows that the levers compound.

Volatility, attention and the loss gradient

Figure 9 tracks daily orders over one simulated year. High-volatility days (about 13% of the year) raise order volume by about 54% under A and 49% under B relative to calm days. The proportional increase is similar. But because A starts from a much higher base, the absolute increase in orders during volatile periods is several times larger. This is when losses are most likely and when a cooling-off mechanism would matter most.

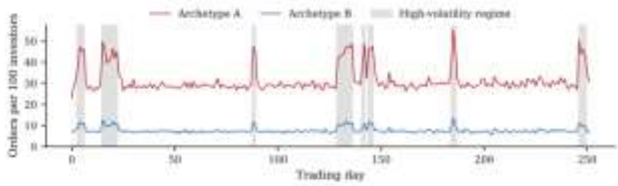

Figure 9: Daily orders per 100 investors over one simulated year. Shaded bands mark high-volatility days.

Figure 10 sorts Archetype A's F&O users by how many F&O orders they placed. The share with a net loss rises steadily from 73.8% in the least active fifth (about 8.5 orders a year) to 98.1% in the most active fifth (about 100 orders). This is partly mechanical, since each F&O order has a negative expected value in the model. It is also consistent with the international evidence that the heaviest traders do worst (Barber and Odean, 2000). The policy implication is direct: any design lever that raises trading frequency moves investors up this gradient.

Econometric validation: can the proposed design detect these effects?

Table 7: Econometric validation on a simulated panel (6,000 investors × 12 months)

	(1) OLS ln(1 + orders) total effect	(2) OLS ln(1 + orders) direct effect	(3) Poisson orders	(4) Poisson F&O orders
AppTime (min/day)	–	0.052***	0.060***	0.079***
		(0.001)	(0.002)	(0.008)
SalienceIndex S	0.624***	0.501***	0.679***	0.696***
	(0.009)	(0.010)	(0.013)	(0.071)
Gamification G	0.331***	0.297***	0.395***	0.318***
	(0.009)	(0.009)	(0.013)	(0.069)
FrictionScore F	−0.069***	−0.068***	−0.089***	−0.199***
	(0.001)	(0.001)	(0.002)	(0.009)
Notifications N	0.085***	0.054***	0.073***	0.061***
	(0.002)	(0.002)	(0.003)	(0.014)
Derivatives prominence D	−0.002	−0.003	0.011	1.158***
	(0.009)	(0.010)	(0.013)	(0.069)
Kill switch K	−0.005	−0.007	−0.012	−0.012
	(0.005)	(0.006)	(0.008)	(0.040)
FOMO scale	0.088***	0.072***	0.108***	0.086***
	(0.003)	(0.003)	(0.004)	(0.019)
Overconfidence scale	0.218***	0.216***	0.286***	0.595***
	(0.002)	(0.002)	(0.004)	(0.017)
log(capital)	0.000	−0.000	0.000	0.009
	(0.003)	(0.003)	(0.004)	(0.019)
log(experience)	−0.006**	−0.007**	−0.003	0.265***
	(0.003)	(0.003)	(0.004)	(0.021)
Month fixed effects	Yes	Yes	Yes	Yes
R^2 / pseudo-R^2	0.376	0.403	0.441	0.299
Observations	72,000	72,000	72,000	72,000

Notes: Standard errors clustered by investor in parentheses. ∗∗∗ $p < 0.01$, ∗∗ $p < 0.05$, ∗ $p < 0.1$. Pseudo-R2 for Poisson models is 1 deviance/null deviance. FOMO and overconfidence scales include measurement noise.

We now apply the planned econometric specifications to simulated data, as if it were survey data. The data have realistic features: each investor has a different design vector, traits are measured with error, and there is market-wide volatility. Table 7 reports the results.

Figure 10: Share of F&O users with a net annual F&O loss, by quintile of F&O order count (Archetype A).

The specifications recover the structure built into the model. Salience, gamification and notifications are positive. Friction is negative: in column (3), each additional step reduces expected orders by about 8.6%. Derivatives prominence has no effect on total orders but a large positive effect on F&O orders in column (4), where the implied effect of moving D from 0 to 1 is about +218%. This matches the volume-versus-mix distinction in the decomposition. Adding AppTime (column 2) reduces the salience coefficient. The share of the salience effect that runs through engagement (Equation 2) is about 20%, and for notifications about 36%, which supports H4.

Two findings are useful warnings for the empirical study. First, the kill-switch coefficient in the pooled panel is small and not significant, even though the model contains a true (small) effect. A cross-sectional survey is therefore unlikely to detect the effect of voluntary friction tools, and a within-platform design is needed. Second, the mediated share is a lower bound on the importance of attention, because AppTime is a noisy proxy for the full attention channel.

For H3, a logit model of F&O activation among the 2,165 simulated novices gives an odds ratio of 0.73 per additional friction step and 8.63 for moving derivatives prominence from 0 to 1.

For H5, Table 8 reports the difference-in-differences design. A kill switch becomes available to a randomly chosen half of an engagement-first platform's users from month 7, with take-up at the baseline assumption. The two-way fixed-effects estimate of θ in Equation (3) is -0.195 F&O orders per investor-month (standard error 0.049), a reduction of about 11.7% relative to the treated group's pre-period mean. Unlike the pooled panel, the design detects the effect clearly, which is why within-platform feature launches should be central to the empirical programme.

Table 8: Difference-in-differences: introduction of a kill switch (F&O orders per investor-month)

Group	Months 1–6	Months 7–12	Change
Control (no kill switch)	1.695	2.762	+1.067
Treated (kill switch from month 7)	1.666	2.537	+0.872
Difference-in-differences			-0.195

Notes: 8,000 simulated investors on Archetype A, randomly split. Two-way fixed-effects estimate: $\hat{\theta} = 0.195$ (clustered s.e. 0.049). The rise in both groups reflects F&O activation accumulating over the year.

Friction interventions and policy counterfactuals

Table 9 and Figure 11 compare interventions applied to the engagement-first design.

Table 9: Friction interventions on the engagement-first design

Scenario	Orders/month	F&O orders/month	Δ F&O vs A (%)	Novice F&O adoption (%)	F&O loss/user (Rs ’000)
A: baseline	6.55	2.10	+0.0	50.7	78.9
A + voluntary kill switch	6.44	1.98	-5.6	50.3	74.5
A + default-on kill-switch prompt	6.24	1.78	-15.2	49.6	61.7
A + F&O cooling-off step	6.04	1.24	-40.7	35.5	59.4
A + cooling-off + default prompt	5.92	1.11	-47.0	35.5	47.3
B: baseline	1.59	0.19	-90.8	13.6	15.7

Notes: 5 replications per scenario. "Default-on prompt" raises kill-switch take-up after a large loss by setting $\kappa 0 = 1$, which corresponds to an opt-out prompt. "Cooling-off" adds a mandatory confirmation step to every F&O order and two steps to F&O activation.

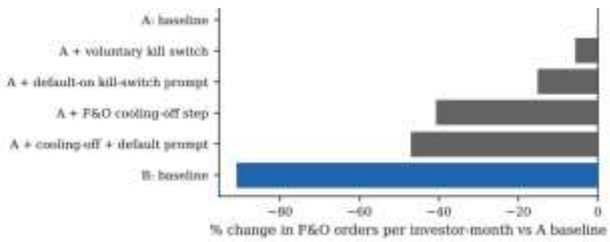

Figure 11: Change in F&O orders per investor-month under alternative interventions, relative to the engagement-first baseline.

The results rank the interventions clearly. A voluntary kill switch reduces F&O orders by only 5.6%. Turning the same tool into a default-on prompt after large losses raises the effect about 2.7-fold (15.2%), which shows how much choice architecture matters (Thaler and Sunstein, 2008). A mandatory cooling-off step on F&O orders is the strongest single measure (40.7%). It also lowers novice F&O adoption to 35.5% and the average F&O loss per user from about Rs 78.9 thousand to Rs 59.4 thousand. Combining the cooling-off step with a default prompt reduces F&O orders by 47.0%. Even so, the engagement-first platform with every intervention stays far above the utility-first baseline, which confirms that the upstream levers (salience, notifications, prominence) do most of the work.

International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
Volume 4, Issue 5, Sep-Oct-2026, PP: 01-12
ISSN:3048-7722

Robustness

The main uncertainty is the size of the behavioural elasticities. Table 10 scales all eleven design-response coefficients together by 0.5 and 1.5.

Table 10: Sensitivity of the A–B gap to the strength of design responses

Elasticity scale	Order ratio A/B	Δ F&O share (pp)	Δ holding (days)	Δ novice adoption (pp)
0.5×	1.94	+8.0	-10.1	+18.0
1.0×	4.11	+19.9	-16.8	+37.1
1.5×	10.68	+36.3	-20.9	+56.9

Notes: Scaled coefficients: θN, θS, θH, αS, αG, αF , βD, βF , γD, k1, k2. 5 replications per setting.

The direction of every result holds across the range. The magnitude does not: the order ratio between the archetypes ranges from 1.94 to 10.68. This is the most important caveat in the paper. The simulation establishes that the framework consistently predicts higher trading, a more speculative mix and shorter holding under engagement-first design. It cannot establish how large these effects are. Only the empirical programme can do that.

Summary of hypothesis tests

Table 11 summarises what the simulation shows and what remains for empirical testing.

Table 11: Hypotheses: simulation evidence and required empirical test

Hypothesis	Simulation result	Decisive empirical test
H1 Salience	Consistent; strong effect on volume, weak effect on mix	Randomised UI experiment (Stage 2)
H2 Gamification	Consistent; holding period falls from 43.9 to 23.7 days	Stage 2 plus survey holding-period data
H3 Friction and novices	Consistent; odds ratio 0.73 per step	Adoption logit on survey; audit-coded *F*
H4 Mediation	Consistent; about 20% of salience effect via AppTime	Screen-time logs with consent
H5 Friction tools	Consistent but small if voluntary (5.6% fewer F&O orders); larger if default-on or mandatory	DiD around a real feature launch

VII. DISCUSSION

Implications for product management

For product managers in fintech, the framework points to a basic tension. The metrics that platforms usually optimise, such as daily active users, sessions and orders, are the same metrics that, beyond a point, predict investor losses. Figure 10 shows why: a design that raises frequency pushes users toward the loss-heavy end of the distribution. We therefore propose an investor-aligned metrics framework for product teams:

1. Pair engagement metrics with outcome metrics. Report net investor P&L (after costs) and the share of users losing money alongside growth dashboards, and give them equal weight in A/B test decisions.
2. Separate volume levers from mix levers. The decomposition shows that derivatives prominence changes what people trade more than how much. Moving F&O entry points away from the default home screen is a low-cost way to reduce speculative exposure without reducing overall engagement.
3. Put friction where it counts. One-time decisions such as F&O activation are the most sensitive to friction (H3). Deliberate friction at these points, such as knowledge checks or loss-statistics disclosures, protects novices at little cost to experienced users.
4. Design protective tools as defaults. The same kill switch is several times more effective as a default-on prompt than as an opt-in setting.

Implications for regulation

SEBI's recent derivatives reforms act on contract design and margins (Securities and Exchange Board of India, 2024a). Our analysis suggests a complementary, interface-level agenda:

- Cooling-off for derivatives orders, at least for investors in their first year of F&O trading, since this was the strongest single intervention in the model.
- Standardised, salient risk disclosure at F&O activation, using SEBI's own loss statis-tics, placed at the point of the one-time decision.
- Guidelines on engagement practices, such as limits on promotional push notifications about specific derivative contracts, following the questions the SEC raised on digital engagement practices (U.S. Securities and Exchange Commission, 2021).
- Mandatory availability, with an opt-out prompt, of loss-limit and kill-switch tools on all platforms, instead of leaving them to the discretion of individual firms.

Any such measures must be weighed against real benefits. Low friction and clear design have brought millions of first-time investors into the market, many into long-term equity and mutual fund investing. The goal is targeted friction on high-risk products, not a return to high-friction investing in general.

A critical perspective

Three points qualify our argument. First, design is not destiny. Investor traits, market conditions and social influences, such as social-media "finfluencers", also drive trading, and the model includes only some of these. Second, causation may run both ways: platforms may add engagement features because their users already want to trade, which is exactly the selection problem in Figure 4. Third, "engagement-first" is not a moral label. Several of the features in Archetype A, such as simplicity, clear visuals and fast execution, are good design in most contexts. The concern is their interaction with a product, short-dated options, whose expected value for retail buyers is negative.

VIII. LIMITATIONS

1. Simulated, not observed, data. All quantitative results come from an agent-based model with assumed parameters. They are predictions and a check of the research design, not empirical findings about real investors or platforms.
2. Calibration. Parameters were chosen to produce plausible activity levels and loss rates close to SEBI's

figures. Other parameter sets could fit these targets and imply different magnitudes (Section 6.7).

3. Stylised archetypes. Archetypes A and B are not measurements of Zerodha, Groww or any other firm. Attributing effects to real platforms requires the design audit and empirical stages.

4. Simplified market and product structure. The model has one market factor, treats F&O as option buying, books P&L at order time, and ignores price impact, option selling, margin calls, investors leaving the market and learning from experience.

5. Behavioural channels. FOMO, overconfidence and loss-chasing are represented as reduced-form terms. Other channels, such as social influence and finfluencers, are omitted.

6. Empirical programme risks. Self-reported trading data are noisy, samples recruited through investor communities may over-represent active traders, and the laboratory experiment's external validity is limited.

IX. CONCLUSION AND FUTURE RESEARCH

This paper argues that the interface through which Indian retail investors reach the market is itself a determinant of how they trade. We broke platform design into six levers, linked each to established behavioural mechanisms, and built an agent-based model that turns the resulting framework into testable predictions. Under our assumptions, engagement-first design produces several times more trading, a more speculative mix, shorter holding periods and much higher derivatives adoption among novices. Salience and notifications mainly drive trading volume. Derivatives prominence and friction mainly drive exposure to F&O. Voluntary friction tools help little unless they are designed as defaults. The model also shows which parts of the empirical design are likely to succeed: randomised interface experiments and within-platform difference-in-differences identify these effects, while cross-sectional comparisons of voluntary tools are unlikely to.

Future work should (i) carry out the design audit of leading Indian applications, (ii) run the randomised interface experiment, (iii) use any future broker-level or regulatory data on trading and app usage to calibrate the model's elasticities, and (iv) extend the model to include social influence, option selling and investor exit. Taken together, these steps would put the regulation of retail derivatives trading on a stronger empirical footing and give fintech product teams a practical basis for investor-aligned design.

A Ethics and Data Protection for the Empirical Programme

The empirical stages involve human participants and sensitive financial behaviour. The protocol will: obtain institutional ethics approval before data collection; use informed consent that explains voluntary participation and the right to withdraw; collect trading history only in aggregate form (orders per month, segment mix, holding period), never broker credentials, account numbers or statements; store data pseudonymised and encrypted, in line with the Digital Personal Data Protection Act, 2023 (Government of India, 2023); use only fictitious money in the simulated-trading experiment; and give participants a debrief with neutral information on derivatives risk.

B Survey Instrument Outline

1. **Platform and usage:** primary and secondary broking apps; average daily sessions; daily minutes on the app (screen-time screenshot optional); notification settings.
2. **Trading behaviour**: orders per month by segment; typical holding period; F&O activation date; use of kill switch or loss limits.
3. **Psychometric scales:** DOSPERT financial sub-scale (Weber et al., 2002); FOMO scale (Przybylski et al., 2013); a trading-overconfidence item set; the "Big Three" financial literacy questions (Lusardi and Mitchell, 2014).
4. **Controls:** age band, city tier, income band, years of market experience, approximate trading capital band.

C Reproducibility

The model is implemented in Python (NumPy, pandas, statsmodels, matplotlib). The file model/abm.py contains the agent-based model. The file model/experiments.py runs every experiment and writes all figures (figures/) and all tables and in-text numbers (generated/), which this document reads directly. Running python3 experiments.py and then recompiling the LATEX source therefore reproduces the paper exactly. Random seeds are fixed.

REFERENCES

1. Angrist, J. D. and Pischke, J.-S. (2009). Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press, Princeton, NJ.
2. Barber, B. M., Huang, X., Odean, T., and Schwarz, C. (2022). Attention-induced trading and returns: Evidence from Robinhood users. Journal of Finance, 77(6):3141–3190.
3. Barber, B. M. and Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance, 55(2):773–806.
4. Barber, B. M. and Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. Quarterly Journal of Economics, 116(1):261–292.
5. Barber, B. M. and Odean, T. (2002). Online investors: Do the slow die first? Review of Financial Studies, 15(2):455–487.
6. Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies, 21(2):785–818.
7. Baron, R. M. and Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 51(6):1173–1182.
8. Benartzi, S. and Thaler, R. H. (1995). Myopic loss aversion and the equity premium puzzle.

9. Quarterly Journal of Economics, 110(1):73–92
10. Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the National Academy of Sciences, 99(suppl. 3):7280–7287.
11. Business Standard (2023). Groww topples Zerodha to become largest broker in terms of number of clients. Business Standard, 12 October 2023.
12. Chapkovski, P., Khapko, M., and Zoican, M. (2026). Trading gamification and investor behavior.
13. Management Science, 72(1):32–56.
14. Eaton, G. W., Green, T. C., Roseman, B. S., and Wu, Y. (2022). Retail trader sophistication and stock market quality: Evidence from brokerage outages. Journal of Financial Economics, 146(2):502–528.
15. Eyal, N. (2014). Hooked: How to Build Habit-Forming Products. Portfolio/Penguin, New York.
16. Ferster, C. B. and Skinner, B. F. (1957). Schedules of Reinforcement. Appleton-Century-Crofts, New York.
17. Gervais, S. and Odean, T. (2001). Learning to be overconfident. Review of Financial Studies, 14(1):1–27.
18. Government of India (2023). The digital personal data protection act, 2023. Act No. 22 of 2023.
19. Grinblatt, M. and Keloharju, M. (2009). Sensation seeking, overconfidence, and trading activity.
20. Journal of Finance, 64(2):549–578.
21. Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk.
22. Econometrica, 47(2):263–291.
23. Kalda, A., Loos, B., Previtero, A., and Hackethal, A. (2021). Smart(phone) investing? A within investor-time analysis of new technologies and trading behavior. NBER Working Paper 28363, National Bureau of Economic Research.
24. Liao, L., Wang, Z., Xiang, J., Yan, H., and Yang, J. (2021). User interface and firsthand experience in retail investing. Review of Financial Studies, 34(9):4486–4523.
25. Lusardi, A. and Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. Journal of Economic Literature, 52(1):5–44.
26. Mathur, A., Acar, G., Friedman, M. J., Lucherini, E., Mayer, J., Chetty, M., and Narayanan, A. (2019). Dark patterns at scale: Findings from a crawl of 11K shopping websites. Proceedings of the ACM on Human-Computer Interaction, 3(CSCW):1–32.
27. Odean, T. (1999). Do investors trade too much? American Economic Review, 89(5):1279–1298.
28. Przybylski, A. K., Murayama, K., DeHaan, C. R., and Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. Computers in Human Behavior, 29(4):1841–1848.
29. Securities and Exchange Board of India (2024a). Measures to strengthen equity index derivatives framework for increased investor protection and market stability. SEBI circular, 1 October 2024.
30. Securities and Exchange Board of India (2024b). Updated SEBI study reveals 93% of individual traders incurred losses in equity F&O between FY22 and FY24; aggregate losses exceed Rs
31. 1.8 lakh crores over three years. Press release, 23 September 2024.
32. Securities and Exchange Board of India (2025). Study on trading activity of individual traders in the equity derivatives segment (FY25). SEBI study, 7 July 2025; as reported by Business Standard.
33. Thaler, R. H. and Sunstein, C. R. (2008). Nudge: Improving Decisions about Health, Wealth, and Happiness. Yale University Press, New Haven, CT.
34. Thaler, R. H., Tversky, A., Kahneman, D., and Schwartz, A. (1997). The effect of myopia and loss aversion on risk taking: An experimental test. Quarterly Journal of Economics, 112(2):647–661.
35. U.S. Securities and Exchange Commission (2021). Request for information and comments on broker-dealer and investment adviser digital engagement practices, related tools and methods, and regulatory considerations and potential approaches. Release No. 34-92766, August 2021.
36. Weber, E. U., Blais, A.-R., and Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. Journal of Behavioral Decision Making, 15(4):263–290.
37. Welch, I. (2022). The wisdom of the Robinhood crowd. Journal of Finance, 77(3):1489–1527. Zerodha (2021). Introducing kill switch. Z-Connect blog, 9 June 2021.