

The Fintech Cascade: Conceptualising App-Driven Herd Behaviour in the Indian Stock Market through Nudge Theory

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ABSTRACT

The rapid proliferation of mobile trading and investment applications has transformed the way Indian retail investors access equity markets. Discount broking platforms, gamified user interfaces, and algorithm-driven notification systems have lowered participation costs while reshaping the psychological environment in which investment decisions are made. This conceptual paper proposes the “FinTech Cascade” framework, which integrates nudge theory with informational and reputational herd-behaviour models to explain how the choice architecture embedded in Indian investment applications may amplify herd behaviour among retail investors. Drawing on an integrative review of behavioural economics, financial herding, and digital choice-architecture literature, the paper identifies four structural gaps in existing research: the absence of an India-specific, app-level theoretical model; insufficient attention to the interaction between gamification and cultural risk attitudes; the lack of a unifying construct linking micro-level nudges to macro-level market cascades; and an underdeveloped regulatory vocabulary for distinguishing beneficial nudges from exploitative “dark nudges” in financial applications. The proposed framework conceptualises four sequential, cyclically reinforcing stages—nudge exposure, cognitive shortcut activation, social-proof amplification, and cascade materialisation—through which individual-level digital nudges may aggregate into collective market behaviour, subject to identification challenges discussed in Section 7. The paper introduces the dark-to-constructive nudge ratio as an operational regulatory construct and concludes with theoretical, managerial, and policy implications, along with an agenda for future empirical validation in the Indian context.

Keywords: Nudge Theory; Digital Nudging; Herd Behaviour; FinTech; Retail Investors; Indian Stock Market; Choice Architecture; Behavioural Finance; Gamification; Dark Patterns

JEL Classification: G11, G40, G41, G18, D91, O33

INTRODUCTION

India’s capital market has undergone a structural transformation over the last decade. The number of demat accounts held with depositories has grown from roughly 39 million in 2019 to over 185 million by the end of 2024, and to approximately 210 million (21 crore) by October 2025 ([Business Standard, 2025](#); DT Next, 2025), a more than fivefold increase in six years, driven substantially by the entry of mobile-first discount broking platforms such as Zerodha, Groww, Upstox, and Angel One. This growth was not merely a function of falling brokerage costs or rising financial literacy; it also stemmed from interface design choices that made investing frictionless, socially visible, and, at times, entertaining. Push notifications announcing “trending stocks,” real-time leaderboards, one-tap order execution, and celebratory animations upon trade completion are now standard features of Indian investment applications.

These design elements are not neutral. They constitute what [Thaler and Sunstein \(2008\)](#) termed “choice architecture,” the deliberate structuring of the context in which decisions are made so as to influence outcomes without restricting options. Their extension into digital interfaces has since been formalised as “digital nudging,” the use of user-interface design elements to guide behaviour in digital choice environments ([Weinmann,](#)

[Schneider, & vom Brocke, 2016](#); [Schneider, Weinmann, & vom Brocke, 2018](#)). When applied to financial applications, digital nudges can, in principle, encourage prudent behaviour such as diversification or periodic investing. However, the same architecture can also be designed, deliberately or otherwise, to encourage impulsive trading, excessive risk-taking, and imitative behaviour.

Herd behaviour, the tendency of investors to mimic the actions of others rather than rely on independent analysis, has long been recognised as a driver of asset mispricing and market instability ([Banerjee, 1992](#); [Bikhchandani, Hirshleifer, & Welch, 1992](#); [Bikhchandani & Sharma, 2000](#); [Scharfstein & Stein, 1990](#)). Traditional explanations of herding in financial markets have emphasised informational cascades, reputational concerns among fund managers, and social conformity pressures operating largely offline or through slow-moving information channels such as news media and word of mouth. The emergence of app-mediated trading introduces a qualitatively different mechanism: herding that can be engineered in real time through algorithmically curated social signals embedded directly in the transaction interface. Empirical work on the Robinhood platform provides a directly relevant precedent here: [Barber, Huang, Odean, and Schwarz \(2022\)](#) show, using outage-based and market-capitalisation discontinuity designs, that a single interface feature, the “Top Movers” list, causally concentrates retail attention and buying in a small set of salient stocks, and that this attention-induced buying predicts subsequent negative abnormal returns. We propose, as a testable rather than an established claim, that a “most bought today” widget or a trending-stocks ticker may compress the informational cascade process described by [Bikhchandani et al. \(1992\)](#) into a much shorter time horizon than classical cascades, for a demographic of investors, young, first-time, and often financially under-literate ([National Centre for Financial Education \[NCFE\], 2019](#); [Molla & Das, 2024](#)), who are especially susceptible to social-proof heuristics ([Kahneman & Tversky, 1979](#)). We note, however, that this compression effect has not itself been directly measured, and [Welch \(2022\)](#) offers a more benign counter-reading in which Robinhood-era retail flow shows limited destabilising effect on prices, a tension the framework addresses explicitly in Section 7.

Despite the scale of this transformation, the academic literature has not yet produced an integrated conceptual account of how app-level nudges translate into market-level herd behaviour in the Indian context. Existing herding studies in India are predominantly empirical and market-data driven, testing for the statistical signature of herding using cross-sectional dispersion measures such as the cross-sectional absolute deviation (CSAD) and cross-sectional standard deviation (CSSD) of returns ([Christie & Huang, 1995](#); [Chang, Cheng, & Khorana, 2000](#)), with mixed findings in the Indian market: some studies report evidence of herding concentrated in specific structural-break or high-volatility periods ([Prosad, Kapoor, & Sengupta, 2012](#)), while others, using more recent samples, report no significant market-wide herding once institutional-investor dominance is accounted for ([Kanojia, 2020](#); [Gupta & Kohli, 2021](#)). Existing nudge-theory literature, meanwhile, is largely situated in public policy, health, and retirement-savings contexts rather than in high-frequency, app-mediated retail trading. The literature on gamification of investment platforms is emerging rapidly in North American and European regulatory contexts ([Barber et al., 2022](#); [Chapkovski, Khapko, & Zoican, 2024](#); [Mathur et al., 2019](#); [Rakovic & Inal, 2023](#)) but has barely been examined with reference to the Indian regulatory and cultural environment. This paper addresses that gap by proposing a conceptual model, the FinTech Cascade, that connects micro-level behavioural nudges embedded in trading-app interfaces to macro-level herd behaviour observed in the Indian stock market, while explicitly identifying the challenges such a model must eventually confront.

The remainder of the paper is organised as follows. Section 2 provides background on the growth of app-based retail investing in India and the regulatory context within which it operates, updated to reflect regulatory developments through 2025-2026. Section 3 reviews the literature on nudge theory, herd behaviour in financial markets, and digital choice architecture in FinTech applications, synthesises it in tabular form (Table 1), and identifies specific research gaps arising from this review. Section 4 outlines the conceptual research methodology adopted in this paper. Section 5 presents the proposed FinTech Cascade framework in detail (Figure 1), links each research gap to a corresponding theoretical proposition, and addresses causal-direction concerns. Section 6 discusses the framework's implications for theory, practice, and policy, followed by limitations, directions for future empirical research, and a concluding summary.

BACKGROUND

The Growth of Investment Apps in India

The Indian retail investment landscape has been reshaped by three concurrent developments: the digitisation of Know-Your-Customer (KYC) and account-opening processes, the entry of low-cost discount brokers operating primarily through mobile applications, and a demographic shift toward a younger, digitally native investor base. The COVID-19 pandemic accelerated this shift considerably, as lockdown-induced idle time, falling fixed-deposit interest rates, and a sharp market correction followed by a rapid recovery in 2020–2021 drew millions of first-time investors into equities, often through smartphone applications rather than traditional broker relationships. Depository data corroborate the scale of this shift: demat accounts rose from roughly 15.1 crore in March 2024 to 21.0 crore by October 2025, with CDSL alone adding tens of lakhs of new accounts most months during this period ([Business Standard, 2025](#); [SBI Securities, 2024](#)). Regulatory bodies such as the Securities and Exchange Board of India (SEBI) have since expressed concern over the growing share of young, inexperienced traders in high-risk segments such as intraday trading and derivatives, prompting circulars aimed at risk disclosure and suitability assessment ([SEBI, 2023b](#)).

How Indian Investment Apps Are Designed and Their Features

Contemporary Indian trading and investment applications share several common design characteristics that are relevant to a nudge-theoretic analysis. First, onboarding flows are typically streamlined to minimise the number of steps between download and first trade, consistent with the nudge principle of reducing friction for a targeted behaviour. Second, many applications incorporate social and gamified elements, including “most traded stocks” lists, portfolio comparison features, achievement badges, and celebratory visual or auditory feedback upon completing a transaction, that mirror the gamification patterns documented in Western trading applications such as Robinhood ([Barber et al., 2022](#); [Chapkovski et al., 2024](#)). Third, push notification systems are used extensively to prompt reengagement, often framed around price movements, market news, or other users' trading activity. Fourth, default settings, such as pre-selected order types, suggested investment amounts, or auto-populated “quick buy” quantities, function as defaults in the classic nudge sense, exploiting status quo bias to steer user behaviour ([Thaler & Sunstein, 2008](#); [Weinmann et al., 2016](#)).

Regulatory and Cultural Context

India's regulatory framework for investor protection has historically focused on disclosure-based regulation, margin requirements, and suitability norms rather than on the psychological design of digital interfaces. This has begun to change, however. In May 2023, SEBI mandated that all stockbrokers display, prominently and covering at least half the screen, statutory risk disclosures showing that the large majority of individual traders in the equity Futures & Options (F&O) segment incur net losses, a study covering FY2021–22 found roughly 9 in 10 individual F&O traders lost money, a figure that a follow-up SEBI study for FY2024–25 confirmed at a similar (91–93%) rate ([SEBI, 2023a, 2023b](#); [NISM, 2026](#)). In May 2025, SEBI further tightened intraday position-limit monitoring and derivative-eligibility rules explicitly in response to elevated retail participation in index derivatives ([SEBI, 2025](#)). Separately, SEBI has, since 2025, taken repeated enforcement action against unregistered “finfluencers” coordinating stock promotion across X, Telegram, and WhatsApp, including a 2026 interim order against a network alleged to have manipulated 82 securities and extracted roughly ₹20 crore in wrongful gains via coordinated social-media amplification ([ANI, 2026](#)). Independent audits nonetheless find that only 2–6% of prominent Indian finfluencers are SEBI-registered even though roughly a third issue explicit stock recommendations ([Business Standard, 2025, 2026](#)), indicating that enforcement capacity still lags the scale of informal social amplification. Taken together, these developments show that SEBI has begun to regulate the downstream consequences of digitally-mediated retail behaviour (disclosure mandates, position limits, finfluencer enforcement) without yet articulating a general vocabulary, comparable to the U.S. Massachusetts fiduciary-rule action against gamified trading-app design ([Berkeley Technology Law Journal, 2026](#)) or the European Securities and Markets Authority's digital-engagement-practices discussion papers, for evaluating in-app interface design itself. Research Gap 4 (Section 3.4) addresses this narrower, more precisely bounded gap.

This regulatory gap is compounded by cultural factors specific to the Indian retail investment context. India's Hofstede Individualism/Collectivism score is 24, an intermediate position rather than an extreme collectivist score, while its Power Distance score of 77 is comparatively high ([Hofstede Insights, n.d.](#)). We therefore reframe the cultural claim made in the original draft: rather than asserting unqualified "high collectivism," the framework proposes that India's combination of moderate collectivist orientation and high power/status deference, together with strong intergenerational and peer-network influence on financial decisions and the widespread use of social media and messaging platforms (such as Telegram and WhatsApp investment groups), interacts with in-app social-proof signals to amplify herd dynamics. This interaction between engineered in-app nudges and pre-existing socio-cultural propensities toward conformity and deference, rather than collectivism alone, motivates the conceptual framework developed in this paper. Persistently low financial literacy (approximately 27% nationally per the NCFE-FLIS 2019 survey; [NCFE, 2019](#); [Molla & Das, 2024](#)) plausibly compounds this susceptibility, though this interaction is itself proposed rather than demonstrated.

LITERATURE REVIEW

Nudge Theory and Choice Architecture

Nudge theory, formally introduced by [Thaler and Sunstein \(2008\)](#), rests on the premise that human decision-making departs systematically from the rational-actor model assumed by classical economics. Drawing on the dual-process account of cognition, in which fast, automatic "System 1" thinking is distinguished from slow, deliberative "System 2" reasoning, Thaler and Sunstein argue that most everyday decisions, including many financial decisions, are made using System 1 heuristics, a distinction with roots in [Kahneman and Tversky's \(1979\)](#) prospect theory and later synthesised for finance specifically by [Barberis and Thaler \(2003\)](#). Choice architects, whether policymakers, employers, or, increasingly, application designers, can therefore steer behaviour by altering defaults, framing information, or introducing social-proof cues, without eliminating any option or imposing significant economic incentives.

Within financial contexts, nudge theory has been applied extensively to retirement savings (for example, automatic enrolment and escalation in pension schemes) and to consumer credit disclosure, but its application to active trading environments remains comparatively underdeveloped. The extension of nudge theory to digital environments has given rise to the concept of the "digital nudge," formally defined as "the use of user-interface design elements to guide people's behaviour in digital choice environments" ([Weinmann et al., 2016](#), p. 433; see also [Schneider et al., 2018](#)). Because digital nudges can be deployed, tested, and iterated at scale and at near-zero marginal cost, they raise novel concerns regarding the intensity and pervasiveness of behavioural influence compared with the physical-world nudges originally discussed by Thaler and Sunstein.

Herd Behaviour in Financial Markets

Financial economics has studied herd behaviour through two broad theoretical lenses: informational and reputational. Informational herding models, most notably the cascade model of [Bikhchandani et al. \(1992\)](#), the related model of [Banerjee \(1992\)](#), and the survey treatment of [Bikhchandani and Sharma \(2000\)](#), demonstrate that rational agents acting sequentially and observing the actions (but not the private information) of predecessors may rationally choose to ignore their own private signals and imitate the crowd once a sufficient number of prior agents have acted similarly. Once such an informational cascade begins, it can persist even when it leads most participants toward a suboptimal or incorrect decision, because no individual has an incentive to deviate. Reputational herding models, exemplified by [Scharfstein and Stein \(1990\)](#), explain herding among professional fund managers as a rational response to career-concern incentives. [Devenow and Welch \(1996\)](#) provide an early synthesis of these "rational herding" explanations, contrasting them with behavioural or "irrational" herding rooted in psychological conformity pressures rather than Bayesian updating.

Empirically, researchers most commonly test herding using cross-sectional dispersion measures of returns. [Christie and Huang \(1995\)](#) proposed the cross-sectional standard deviation (CSSD), arguing that herding compresses individual asset returns toward the market average during periods of market stress, producing an abnormally low CSSD. [Chang, Cheng, and Khorana \(2000\)](#) refined this into the cross-sectional absolute deviation (CSAD), which is more robust to outliers and remains the dominant methodology in the Indian

literature. Applying these methods, [Prosad et al. \(2012\)](#) found evidence consistent with herding in the Indian equity market during periods of high volatility, while more recent studies using longer or more recent samples report mixed or null results: [Kanojia \(2020\)](#) finds no significant market-wide herding across a decade of Indian data, attributing this to the dominance of institutional investors and comparatively low retail participation in the sample period studied, and [Gupta and Kohli \(2021\)](#) similarly report limited evidence of sustained herding outside specific structural-break windows. This mixed empirical record is important context for the FinTech Cascade framework: the framework does not assume herding is a settled, omnipresent feature of the Indian market, but rather proposes conditions (namely, high digital nudge exposure and social-proof amplification) under which herding becomes more likely to be observed, a scope condition that reconciles the framework with the null and mixed findings noted above. Subsequent studies examining herding among individual Indian retail investors, rather than at the aggregate market level, have used survey-based and mixed-method approaches to identify psychological and social antecedents of herding, including fear of missing out, social influence, overconfidence, and low financial literacy ([Nair, Balasubramanian, & Yermal, 2017](#); [Kumar, Bharti, & Bansal, 2016](#)). More recent thematic reviews of the global herd-behaviour literature note that the field remains dominated by studies conducted in developed markets and by studies that treat herding as a statistical property of returns rather than as a behavioural process shaped by the information environment in which investors operate ([Bharti & Kumar, 2025](#)). This observation is particularly salient for the Indian context, where the information environment for a large and growing share of retail investors is now mediated primarily through a smartphone application rather than through a broker, financial advisor, or print or broadcast media.

Gamification, Dark Patterns, and Digital Engagement in FinTech Applications

A distinct but closely related literature has emerged around the gamification of trading applications and its behavioural consequences. Gamification refers to the incorporation of game-design elements, points, badges, leaderboards, progress bars, and celebratory feedback, into non-game contexts to increase user engagement. In the trading-app context, [Chapkovski, Khapko, and Zoican \(2024\)](#) conducted a randomised experiment comparing trading behaviour on gamified and non-gamified simulated trading platforms and found that hedonic gamification features such as confetti animations and achievement badges materially increased trading volume, with the effect concentrated among participants with lower financial literacy. The most direct empirical precedent for the present framework, however, comes from [Barber, Huang, Odean, and Schwarz \(2022\)](#), who use Robinhood service outages and a market-capitalization regression-discontinuity design to show that the app's "Top Movers" list, a widget structurally similar to the "trending stocks" tickers common on Indian apps, causally concentrates retail attention and buying, and that this attention-induced buying forecasts negative 20-day abnormal returns of roughly -4.7% on average for the most-purchased stocks each day. This finding lends direct empirical plausibility to the mechanism proposed in Stage 3 of the FinTech Cascade (Section 5.3). At the same time, [Welch \(2022\)](#), examining the same population of Robinhood users over the COVID-19 period, finds that aggregate retail order flow shows limited ability to move prices and that Robinhood users' collective portfolio choices were not obviously irrational in aggregate, a more benign reading that the present framework should not ignore. This finding is consistent with earlier concerns, raised in the aftermath of the 2021 "meme stock" episode involving Robinhood, that gamified interfaces encourage frequent, low-deliberation trading, but the evidence base is more contested than a single-sided narrative would suggest.

Related work on "dark patterns", user-interface designs that manipulate users into decisions they would not otherwise make, a term coined by [Brignull \(2023\)](#), has documented the prevalence of such patterns across e-commerce platforms ([Mathur et al., 2019](#)) and, more recently, in digital investment platforms specifically. [Rakovic and Inal \(2023\)](#), examining 26 investment apps available in Norway, found that non-bank fintech apps embed markedly more dark patterns than traditional bank-operated apps, particularly around data-sharing defaults and cost transparency, a directly relevant comparative benchmark for future empirical work on Indian discount brokers, none of which currently exists. Regulatory and behavioural-science bodies, including the Behavioural Insights Team and the Ontario Securities Commission, have distinguished between "digital engagement practices" that may benefit investors, such as helpful reminders or educational prompts, and "dark nudges" or "sludge," which use similar design techniques to steer users toward actions, such as more frequent trading, that primarily benefit the platform rather than the user. Notably, this literature has developed almost entirely with reference to United States, European Union, Canadian, and Norwegian regulatory contexts; the specific design patterns used by Indian trading applications, and their interaction with India's distinctive retail

investor demographic and social information environment, remain largely unexamined in peer-reviewed research.

Synthesis and Identification of Research Gaps

Table 1 synthesises the three literature streams reviewed above and identifies four specific gaps that motivate the conceptual framework developed in this paper.

Table 1. Synthesis of Literature Streams and Corresponding Research Gaps

Research Gap	What the Herding Literature Offers	What the Nudge / Gamification Literature Offers	Resulting Gap Addressed by FinTech Cascade
Gap 1: No India-specific, app-level model	Aggregate CSAD/CSSD evidence for Indian equities (Prosad et al., 2012 ; Kanojia, 2020 ; Gupta & Kohli, 2021)	App-level gamification evidence almost entirely from US/EU platforms (Chapkovski et al., 2024 ; Barber et al., 2022 ; Rakovic & Inal, 2023)	Stage 1 (Digital Nudge Exposure) situates the analysis at the level of specific Indian app interface features
Gap 2: Culture and conformity untheorized	Survey-based antecedents (FOMO, overconfidence) in Indian samples (Nair et al., 2017)	Bias constructs validated mainly in Western/individualist samples; no cultural moderator specified	Stage 2 (Heuristic Activation) proposes conformity orientation as an explicit moderator (Proposition 2)
Gap 3: No micro-to-macro bridging construct	Sequential, market-wide cascade models (Bikhchandani et al., 1992 ; Banerjee, 1992 ; Bikhchandani & Sharma, 2000)	Individual-level UI effects (Weinmann et al., 2016 ; Barber et al., 2022) with no stated aggregation mechanism	Stage 3 (Social-Proof Amplification) specifies algorithmic redisplay as the bridging mechanism (Proposition 3)
Gap 4: No regulatory vocabulary for dark vs. constructive nudges in India	Disclosure-based Indian regulation (SEBI, 2023a, 2023b, 2025); nascent influencer enforcement (ANI, 2026 ; Business Standard, 2025, 2026)	Dark-pattern taxonomies developed outside India (Brignull, 2023 ; Rakovic & Inal, 2023 ; Mathur et al., 2019)	Section 5.5 proposes the dark-to-constructive nudge ratio as an India-specific classificatory construct

Research Gap 1: Absence of an India-specific, app-level theoretical model. The Indian herding literature ([Prosad et al., 2012](#); [Kanojia, 2020](#); [Gupta & Kohli, 2021](#); [Nair et al., 2017](#); [Bharti & Kumar, 2025](#)) has examined herding largely through aggregate market-return statistics or general survey instruments not specific to any application interface, while the gamification and dark-pattern literature ([Barber et al., 2022](#); [Chapkovski et al., 2024](#); [Mathur et al., 2019](#); [Rakovic & Inal, 2023](#)) has developed primarily outside the Indian context. No study in this review connects the specific design features of Indian trading applications to the herding mechanisms documented in the Indian market; we note this absence in the reviewed literature rather than claiming literal non-existence.

Research Gap 2: Insufficient attention to the interaction between gamification and culturally embedded risk and conformity attitudes. Nudge and gamification research has generally treated user psychology as culturally uniform, relying on cognitive-bias constructs (loss aversion, availability, social proof) developed and validated primarily in Western samples. India's intermediate collectivism score alongside its high power-distance score ([Hofstede Insights, n.d.](#)), together with strong peer and family influence over financial decisions and the parallel use of informal social-media investment communities ([ANI, 2026](#); [Business Standard, 2025, 2026](#)), are not

incorporated into existing nudge or herding models, despite plausibly moderating the strength and speed with which app-based nudges translate into imitative behaviour.

Research Gap 3: Lack of a unifying construct linking micro-level nudges to macro-level market cascades. Herding models such as those of [Bikhchandani et al. \(1992\)](#) and [Banerjee \(1992\)](#) operate at the level of sequential, market-wide decision-making, while nudge and gamification research, including the causal Robinhood evidence in [Barber et al. \(2022\)](#), operates at the level of individual user interaction with a single application. No existing conceptual model specifies the intermediate mechanisms, such as the aggregation of individually nudged decisions into visible, platform-level social-proof signals, through which micro-level digital nudges could plausibly scale into macro-level, market-wide herding episodes, while also accounting for the reverse-causal possibility that platform signals merely reflect, rather than cause, pre-existing market-wide movements ([Welch, 2022](#)).

Research Gap 4: Underdeveloped regulatory vocabulary for distinguishing beneficial from exploitative financial nudges in the Indian context. As detailed in Section 2.3, SEBI has begun to address specific downstream harms (F&O losses, influencer manipulation) through disclosure mandates and enforcement actions ([SEBI, 2023a, 2023b, 2025](#); [ANI, 2026](#)), but India's regulatory literature does not yet provide a general conceptual vocabulary or classificatory framework, comparable to international "digital engagement practices" or "dark pattern" taxonomies, for evaluating the design of Indian trading-application interfaces on these terms.

Section 5 addresses these four gaps directly by linking each gap to a specific structural component of the proposed FinTech Cascade model.

RESEARCH METHODOLOGY

This paper adopts a conceptual research design, appropriate for theory-building contributions in management and behavioural-finance scholarship where the objective is to synthesise disparate literatures into a novel, testable framework rather than to test hypotheses against data ([MacInnis, 2011](#)). Following [Jaakkola's \(2020\)](#) typology of conceptual-article designs, this paper most closely follows the "theory synthesis" approach, integrating established but previously unconnected theoretical streams into a new explanatory model. The methodology follows three sequential stages: an integrative literature review, construct identification and definition, and framework articulation with propositions.

Stage 1: Integrative literature review. A purposive, narrative review (as opposed to a systematic or meta-analytic review) was conducted across three literature streams identified as jointly relevant to the research problem: (a) foundational and applied nudge-theory and digital-choice-architecture literature, (b) informational and reputational herding models in financial economics together with empirical herding studies conducted in the Indian equity market, and (c) the emerging literature on gamification, digital engagement practices, and dark patterns in FinTech and trading-application design. We drew sources from peer-reviewed journals in finance, economics, and information systems, along with reports from recognised behavioural-science and regulatory bodies (including SEBI circulars and studies), where peer-reviewed academic sources on app-specific gamification were still emerging. We note as a limitation that this narrative approach, rather than a systematic review protocol (e.g., PRISMA), means the "absence" claims in Section 3.4 should be read as gaps in the literature identified through this review rather than as exhaustively verified non-existence claims.

Stage 2: Construct identification and definition. From the integrative review, four core constructs were identified as necessary building blocks for a unifying framework: (i) digital nudge exposure, defined as the frequency and salience of choice-architecture elements (defaults, notifications, social-proof widgets, gamified feedback) encountered by a user within a trading application; (ii) heuristic activation, defined as the triggering of System 1 cognitive shortcuts (social proof, availability, loss aversion, FOMO) as a consequence of nudge exposure; (iii) social-proof amplification, defined as the aggregation and algorithmic redisplay of individual user behaviours (such as trending-stock or most-bought lists) back to the wider user base, creating a feedback loop between individual and collective behaviour; and (iv) cascade materialization, defined as the observable, market-level herding outcome, abnormal trading volume concentration, correlated buy/sell activity, or short-term price

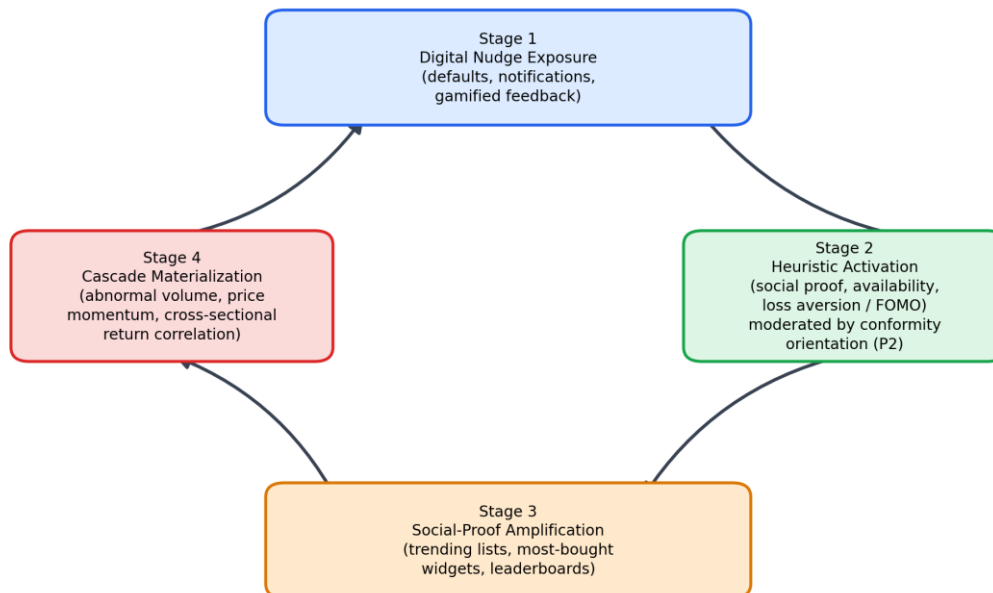
momentum in specific securities , that results when heuristic activation and social-proof amplification operate at sufficient scale across the user base of one or more applications.

Stage 3: Framework articulation. The four constructs were then organised into a sequential, cyclical process model, the FinTech Cascade, and linked explicitly to the four research gaps identified in Section 3.4, with each stage of the model formulated as a set of theoretical propositions suitable for future empirical testing, and with explicit attention to the causal-identification challenges such testing would face (Section 7). Because this is a conceptual rather than empirical paper, no primary data collection, statistical testing, or human-subject research was undertaken; the contribution of the paper lies in the synthesis and structuring of existing theoretical and empirical insights into a novel, internally consistent framework, together with a set of falsifiable propositions to guide subsequent empirical research.

The FinTech Cascade: A Conceptual Framework

The FinTech Cascade framework proposes that app-driven herd behaviour in the Indian stock market may emerge through four sequential, mutually reinforcing stages, forming a cyclical process rather than a one-time linear event, as illustrated in Figure 1. The framework is designed explicitly to close the four research gaps identified above, and each stage is discussed below with its corresponding theoretical proposition.

Figure 1. The FinTech Cascade: A Four-Stage Cyclical Framework



Regulatory boundary condition: the ratio of “dark” to “constructive” nudges embedded at Stage 1 (Section 5.5) determines the framework’s net effect on investor welfare.

Figure 1: Proposed Conceptual Framework Made by the author.

Stage One: Digital Nudge Exposure

The cascade originates in the deliberate choice-architecture decisions embedded in a trading application’s interface: default order quantities, streamlined one-tap execution, push notifications framed around price movements or peer activity, and gamified visual or auditory feedback. Consistent with [Thaler and Sunstein’s \(2008\)](#) account of choice architecture and its digital-nudging extension ([Weinmann et al., 2016](#)), these design elements do not restrict investor options but systematically increase the salience and ease of specific actions, typically initiating a trade. This stage directly addresses Research Gap 1 by situating the analysis at the level of the specific interface features of Indian trading applications rather than treating “the market” as an undifferentiated environment.

Proposition 1: The intensity of digital nudge exposure (frequency of gamified feedback, social-proof widgets, and transaction-facilitating defaults) within an Indian trading application is positively associated with retail users' trading frequency, independent of underlying market fundamentals.

Stage Two: Heuristic Activation

Exposure to digital nudges triggers System 1 cognitive heuristics identified in the prospect-theory and behavioural-finance literature ([Kahneman & Tversky, 1979](#); [Barberis & Thaler, 2003](#)): social proof, availability, and loss aversion interacting with fear of missing out. This stage is where culturally embedded conformity attitudes, reflecting India's intermediate collectivism combined with high power-distance orientation ([Hofstede Insights, n.d.](#)) and reinforced by informal social-media investment communities, are proposed to moderate the strength of heuristic activation, directly addressing Research Gap 2.

Proposition 2: The relationship between digital nudge exposure and heuristic activation is moderated by culturally embedded conformity orientation, such that investors with higher trait or contextual conformity orientation (for example, those embedded in active peer or social-media investment communities) exhibit stronger heuristic activation for a given level of nudge exposure.

Stage Three: Social-Proof Amplification

Individual trading decisions resulting from heuristic activation are not private; the application's backend aggregates them and redisplay them to the broader user base through features such as "most bought today," trending-stock lists, or leaderboard rankings. This stage is the critical mechanism bridging individual-level nudged behaviour and market-wide herding, directly addressing Research Gap 3, and is the stage most directly supported by existing causal evidence: Barber et al. (2022) demonstrate this aggregation-and-redisplay mechanism operating on Robinhood's "Top Movers" widget. Whereas classical informational-cascade models ([Bikhchandani et al., 1992](#); [Banerjee, 1992](#)) describe herding as arising from the sequential observation of predecessors' actions over an unspecified time horizon, the FinTech Cascade framework proposes that trading applications compress and formalise this observational process into a real-time, algorithmically aggregated signal broadcast simultaneously to potentially millions of users, while acknowledging, per [Welch \(2022\)](#), that the direction of causality between platform signals and underlying market movements requires empirical disentangling rather than assumption.

Proposition 3: The presence and visual salience of algorithmically aggregated social-proof signals (trending-stock lists, most-bought widgets) within a trading application accelerates the speed and increases the magnitude of informational cascades, relative to informational environments lacking such real-time aggregated signals, net of confounding market-wide volatility.

Stage Four: Cascade Materialisation

When heuristic activation and social-proof amplification operate at sufficient scale across an application's user base, and particularly when correlated across multiple applications simultaneously, the result is an observable, market-level herding outcome: abnormal concentration of trading volume in specific securities, short-term price momentum disconnected from fundamentals, and elevated cross-sectional return correlation of the type measured using CSAD/CSSD methodologies ([Chang et al., 2000](#); [Christie & Huang, 1995](#); [Prosad et al., 2012](#)). Critically, the FinTech Cascade framework proposes that this stage feeds back into Stage One: elevated trading volume and price momentum in a security become new content for push notifications and trending-stock widgets, which in turn generate a fresh round of nudge exposure, closing the cycle. This feedback loop distinguishes the FinTech Cascade from classical, largely unidirectional herding models.

Proposition 4: Market-level herding episodes in securities heavily featured on Indian trading-application social-proof widgets exhibit a self-reinforcing volume-attention cycle, such that abnormal trading volume increases the probability of subsequent algorithmic promotion (notification, trending-list inclusion), which in turn sustains or amplifies abnormal trading volume for a longer duration than comparable episodes in securities not featured on such widgets, holding market-wide volatility constant.

Regulatory Boundary Conditions

Finally, the framework proposes a classificatory boundary condition addressing Research Gap 4: the distinction between “constructive nudges” and “dark nudges” within the cascade. Constructive nudges, such as diversification prompts, systematic investment plan defaults, or the risk-disclosure interstitials SEBI now mandates for F&O trading ([SEBI, 2023b](#)), are designed to align with the investor’s long-term financial interest. Dark nudges, such as gamified feedback rewarding transaction frequency, social-proof widgets highlighting speculative or high-volatility securities, or defaults that facilitate leveraged or derivative trading without proportionate friction, are those whose design objective or probable effect primarily serves platform engagement or revenue metrics at the expense of investor welfare, a distinction with a documented comparative benchmark in non-Indian markets ([Rakovic & Inal, 2023](#)). The FinTech Cascade framework proposes that the ratio of dark to constructive nudges embedded in an application’s interface is the single most important design-level determinant of the application’s contribution to market-wide herd behaviour, and is therefore proposed as the primary construct around which future regulatory guidance in India could be developed.

FINDINGS, DISCUSSION, AND IMPLICATIONS

As a conceptual paper, this study does not report empirical findings in the traditional sense; rather, its central “finding” is the FinTech Cascade framework itself, together with the four propositions derived from it, offering a structured account of a phenomenon existing literature has addressed only in fragments. Read against the research gaps identified in Section 3.4, the framework makes four contributions, summarised in Table 1.

Theoretical Implications

The framework extends behavioural-finance theory by proposing that herding is not solely a function of the information environment external to a trading platform but is potentially co-produced by the platform’s own interface design, a reconceptualisation directly supported by the causal Robinhood evidence in [Barber et al. \(2022\)](#), though tempered by [Welch’s \(2022\)](#) more benign reading of aggregate retail impact. This reframes the trading application from a neutral transaction channel into a potentially active participant in the herding process, with implications for how future herding research operationalises its independent variables: rather than treating “information availability” as an exogenous market condition, future studies might treat application-level design features as a measurable, manipulable independent variable in their own right, following the outage-based and discontinuity-based identification strategies pioneered in the Robinhood literature.

Managerial Implications

For FinTech platform designers, the framework suggests that gamification and social-proof features, while commercially effective at increasing engagement and trading frequency ([Chapkovski et al., 2024](#)), carry systemic reputational and regulatory risk to the extent that they measurably increase the dark-to-constructive nudge ratio proposed in Section 5.5, a risk already realised in comparable markets, where non-bank fintech apps have been shown to embed markedly more dark patterns than bank-operated apps ([Rakovic & Inal, 2023](#)). Platforms seeking to differentiate themselves on investor-welfare grounds, or to pre-empt regulatory action of the kind already observed against influencer networks in India ([ANI, 2026](#)) and against gamified design internationally ([Berkeley Technology Law Journal, 2026](#)), may find it commercially prudent to voluntarily audit and rebalance their nudge portfolios toward constructive designs.

Policy Implications

For SEBI and allied regulatory bodies, the framework offers a starting vocabulary for extending India’s largely disclosure-based investor-protection regime, already visible in the 2023 and 2025 F&O and derivatives circulars ([SEBI, 2023a, 2023b, 2025](#)) and in ongoing influencer enforcement ([ANI, 2026](#); [Business Standard, 2025, 2026](#)), into the domain of interface design regulation. Given that India’s retail investor base is now overwhelmingly app-mediated ([Business Standard, 2025](#)), the framework suggests that Indian policy discussions could productively draw on international “digital engagement practices” and “dark pattern” classifications

([Brignull, 2023](#); [Rakovic & Inal, 2023](#)), adapting them to India's specific market structure and to the cultural amplification mechanisms proposed at the heuristic-activation stage of the model.

Limitations and Directions for Future Research

As a conceptual contribution, this paper's principal limitation is the absence of empirical validation; the propositions in Section 5 are formulated to be testable but have not themselves been tested. A related and more specific limitation concerns causal identification: the framework as articulated is consistent with digital nudges causing herding, but it is equally consistent with reverse causality (pre-existing market-wide volatility or news driving both organic trading volume and the algorithmic content of trending widgets) and with confounding (unobserved macroeconomic shocks driving both). Future empirical work should therefore prioritise identification strategies analogous to those used by [Barber et al. \(2022\)](#), for example, exploiting platform outages, staggered feature rollouts across Indian apps, or discontinuities in widget-inclusion thresholds, rather than relying on simple correlational designs that cannot distinguish the FinTech Cascade's proposed mechanism from [Welch's \(2022\)](#) more benign alternative reading.

Future research should pursue several complementary strategies. First, controlled behavioural experiments modelled on [Chapkovski et al.'s \(2024\)](#) and [Barber et al.'s \(2022\)](#) methodologies could be adapted to Indian participant samples and application interface replicas to test Propositions 1 and 2. Second, agent-based modelling could simulate the social-proof amplification and cascade-materialisation stages (Propositions 3 and 4) under varying network and algorithmic-design assumptions, without requiring proprietary platform data. Third, mixed-method field studies combining conformity-orientation and social-media-community measures with matched, anonymised brokerage data would allow more direct tests of the full cascade. Fourth, a systematic (rather than narrative) literature review, following an explicit protocol such as PRISMA, would allow the "absence" claims underlying Research Gaps 1–3 to be verified more rigorously than the integrative review conducted here permits. Finally, comparative cross-country research on whether Proposition 2's cultural moderation genuinely distinguishes Indian herding dynamics from less collectivist markets, and a direct replication of [Rakovic and Inal's \(2023\)](#) dark-pattern audit methodology on the leading Indian discount-broking apps, would extend both behavioural-finance and cross-cultural management scholarship and would directly operationalise the dark-to-constructive nudge ratio proposed in Section 5.5.

CONCLUSION

This paper has argued that the dramatic growth of app-based retail investing in India, from roughly 39 million demat accounts in 2019 to over 210 million by late 2025 ([Business Standard, 2025](#); [DT Next, 2025](#)), has created a distinctive behavioural environment in which classical herd-behaviour mechanisms may be mediated, accelerated, and in some respects newly shaped by the choice-architecture decisions embedded in trading-application interfaces. By synthesizing nudge and digital-nudging theory ([Thaler & Sunstein, 2008](#); [Weinmann et al., 2016](#)), informational and reputational herding models ([Banerjee, 1992](#); [Bikhchandani et al., 1992](#); [Scharfstein & Stein, 1990](#)), and the emerging empirical literature on gamification and dark patterns in FinTech design ([Barber et al., 2022](#); [Chapkovski et al., 2024](#); [Mathur et al., 2019](#); [Rakovic & Inal, 2023](#)), the paper has proposed the FinTech Cascade framework, a four-stage cyclical model comprising digital nudge exposure, heuristic activation, social-proof amplification, and cascade materialization, bounded by a regulatory distinction between constructive and dark nudges. Each stage of the framework is explicitly linked to a specific gap in the existing literature and formulated as a falsifiable proposition, with explicit attention to the causal-identification challenges (reverse causality, confounding) that future empirical work on this framework must confront. As Indian retail investors continue to conduct an increasing share of their market activity through smartphone applications, and as SEBI's own recent enforcement record against F&O losses and influencer manipulation illustrates ([SEBI, 2023a](#); [ANI, 2026](#)), understanding the behavioural architecture of those applications is likely to become as important to market stability and investor protection as understanding the fundamentals of the securities being traded. The FinTech Cascade framework offers one conceptual starting point for that understanding, and, it is hoped, a foundation for the empirical research agenda outlined above.

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