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The Architecture Of Irrationality: Behavioural Biases And Sentiment Dynamics In Digital Asset Markets

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Abstract
This paper investigates the extent to which cognitive heuristics, social influence, and digitally-mediated sentiment drive the extreme volatility of cryptocurrency, Decentralised Finance (DeFi), and Non-Fungible Token (NFT) markets, and the degree to which these dynamics deviate from the Efficient Market Hypothesis. Using an integrative narrative review and a synthesis of empirical evidence from 2014–2025, the paper develops the Integrated Digital Asset Behavioural Model (IDABM), a four-variable framework relating market stability to social velocity (S_v), heuristic load (H_l), platform gamma (P_γ), and liquidity leverage (L_l). The analysis draws on demographic and sentiment data, case evidence from the 2022 Terra/Luna and FTX collapses, and a comparative cross-asset bias taxonomy. The findings indicate that digital asset markets constitute a pure sentiment environment in which the absence of conventional valuation anchors produces heuristic dominance and structurally amplified herding behaviour. The paper concludes that effective regulation must shift from informational disclosure toward behavioural guardrails — including algorithmic accountability, regulation of gamified trading interfaces, and behavioural literacy requirements.

Keywords: *behavioural finance; cryptocurrency; digital assets; herding; FOMO; sentiment analysis; Prospect Theory; Adaptive Markets Hypothesis*

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I. Introduction

Since the launch of Bitcoin in 2009 (Nakamoto, 2008), financial markets have been irreversibly altered. From an obscure cryptographic experiment created in response to the 2008 financial crisis, digital assets have emerged as a multi-trillion-dollar market spanning thousands of distinct instruments built on Distributed Ledger Technology (DLT). The asset class is now understood as comprising three loosely-bounded epochs: the *cypher-punk era* (2009–2013) of ideological experimentation; the *speculative expansion* (2014–2020) characterised by Initial Coin Offerings (ICOs), alternative chains, and a globalising retail base; and the *institutional and DeFi era* (2020–present) in which regulated entities, sovereign treasuries, and synthetic financial primitives operate alongside meme-coin speculation.

The history of this market is marked by cycles that defy conventional economic principles. The Decentralised Finance "summer" of 2020, the Non-Fungible Token (NFT) mania of 2021, and the subsequent collapses of the Terra/Luna ecosystem and FTX in 2022 highlight a central paradox: the underlying technology is deterministic, mathematical, and transparent, while its participants are non-deterministic, opaque, and often manipulable (Chen & Bellavitis, 2020; Glassnode, 2024). The shift from value-based investing to narrative-based speculation has elevated behavioural economics to a position of central explanatory power. Traditional financial theory speaks of the rational agent operating with full information and maximising expected utility; the digital asset market, by contrast, appears to be the natural habitat of *Homo Psychologicus*, whose social identity, tribal affiliation, and emotional state routinely override economic principles and risk-management discipline (Shefrin, 2002; Shiller, 2003).

Research Problem and Questions

The central problem addressed in this paper is why digital assets exhibit volatility that cannot be explained or forecast by traditional economic factors or asset-pricing models such as the Capital Asset Pricing Model (Sharpe, 1964). Conventional financial markets possess "objective" inputs to price formation — earnings, dividend yields, interest rates — whereas most digital assets, particularly those without cash flow (Bitcoin, meme coins, generative-art NFTs), possess no such inputs. The resulting *valuation vacuum* is filled by expecta-tions, speculation, and social narratives, producing a fundamentally psychological pricing environment. This is amplified by the 24/7/365 nature of digital asset markets, which lack the cooling-off periods of traditional mar-kets.

The study addresses four research questions:

1. Which behavioural biases most influence the investment decisions of digital-asset investors, and do these vary systematically between retail and institutional participants?
2. How do digital media — social-media echo chambers and mobile trading platforms — accelerate, amplify, and enable herding and Fear of Missing Out (FOMO) dynamics?
3. How does the absence of fundamental valuation ratios in digital assets increase the influence of sentiment-driven heuristics relative to traditional financial assets?
4. How can a multi-dimensional behavioural framework better explain the formation and collapse of crypto-ecosystem bubbles such as the 2021 NFT mania?

Research Gap and Contribution

Although behavioural finance has a long lineage through Kahneman and Tversky (1979), Thaler (2015), and Shiller (2003), its application to digital assets remains fragmented. Existing research tends to focus on a single bias (e.g., herding in Bitcoin; Kumar & Goyal, 2024) or a single asset class (e.g., volatility in Ethereum). What is required is an integrated view that recognises the spectrum of digital assets — store-of-value (Bitcoin), utility (DeFi), and culture (NFTs) — and how distinct biases dominate each sub-class. The literature has also paid limited attention to *platform bias*: the influence of UI/UX design and algorithmic curation on the velocity of sentiment formation. The present paper addresses these gaps through an interdisciplinary approach integrating insights from financial economics, psychology, and socio-technology. Its principal contribution is the *Integ-rated Digital Asset Behavioural Model (IDABM)*, presented in Section 5, which formalises the joint influence of social velocity, heuristic load, platform gamma, and liquidity leverage on market stability.

II. Literature Review

Theoretical Foundations

The behavioural finance of digital assets rests on foundational theories that challenge the Random Walk Hypothesis and the strict-form Efficient Market Hypothesis (Fama, 1970). Three frameworks are central. *Pro-spect Theory* (Kahneman & Tversky, 1979; Tversky & Kahneman, 1974) shows that loss is experienced as approximately twice as painful as equivalent gain is pleasurable; in cryptocurrency contexts this manifests as the disposition effect — investors holding losing positions ("bags") in the hope of return-to-cost while selling winners prematurely. The *Adaptive Markets Hypothesis* (Lo, 2004) treats markets as evolutionary; cryptocur-rency markets, on this view, remain in a "pioneer" phase whose behavioural sensitivity is high because rules are still being negotiated. *Bounded Rationality* (Simon, 1955) implies that, in the complex world of smart contracts and tokenomics, investors must *satisfice* with simplified mental models that are "good enough" but inherently faulty. Figure 1 maps the points at which classical frameworks break down and which behavioural frameworks step in.

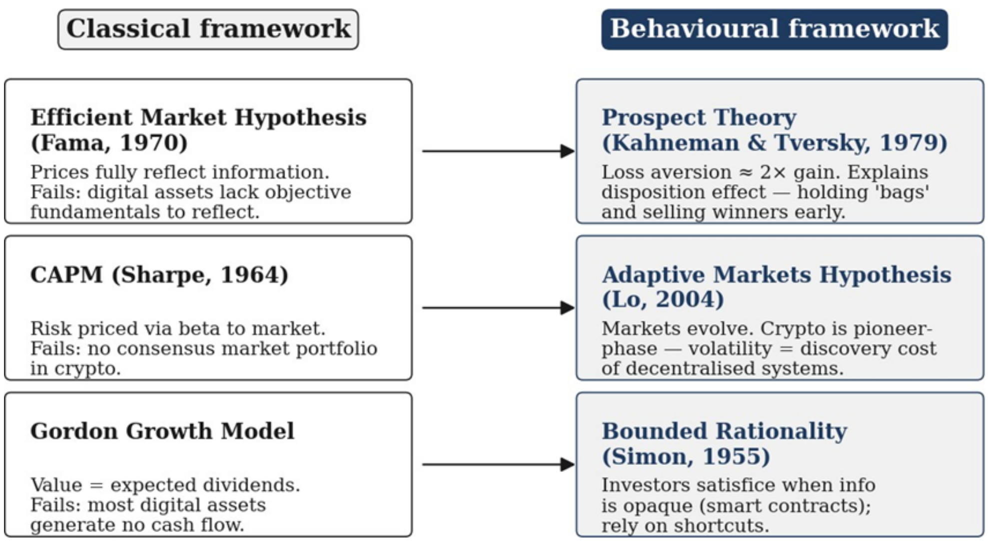

Figure 1. Theoretical frameworks for digital asset markets. Where classical financial theory breaks down (left) and which behavioural framework provides explanatory power (right).

Source: Author's compilation based on Fama (1970), Kahneman & Tversky (1979), Sharpe (1964), Simon (1955), and Lo (2004).

The Theory of Planned Behavior (Kumar et al., 2023; Nadeem et al., 2020) is frequently invoked to explain cryptocurrency adoption, though in this context "perceived behavioural control" is heavily skewed by techno-optimism. The Noise Trader Model (De Long et al., 1990) is particularly germane: it argues that sentiment-driven retail investors can act as a *limit to arbitrage*, so that even rational investors may be forced to follow irrational sentiment to avoid forced liquidation — a dynamic that compounds the irrationality of the market it-self.

Empirical Evidence on Volatility and Sentiment

Realised volatility in digital assets exceeds that of traditional asset classes by an order of magnitude. Figure 2 presents annualised volatility estimates for major digital and traditional assets over the period 2020–2025. Bitcoin and Ethereum realise approximately 62% and 78% annualised volatility respectively, while average meme-coin volatility exceeds 145% — roughly seven times the typical equity volatility regime (Glassnode, 2024).

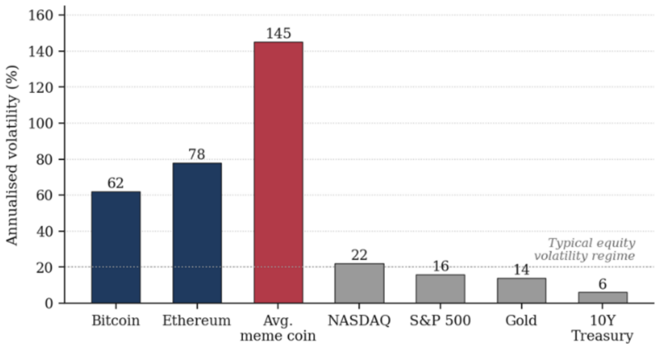

Figure 2. Realised annualised volatility, digital assets versus traditional markets, 2020–2025.
Source: Author's compilation from Glassnode (2024) and major exchange data. Dashed line indicates the typical equity volatility regime (~20%).

Recent empirical work has converged on three productive lines of inquiry. First, social-media sentiment has been shown to lead cryptocurrency price movements. Bollen, Mao, and Zeng (2011) demonstrated that Twitter sentiment can predict equity-market returns; subsequent work has extended the finding to cryptocurrency markets (Nofer & Hinz, 2015; Ranco et al., 2015; Demir et al., 2024), with horizons of 2–3 days and directional accuracy approaching 80% in favourable specifications. Figure 3 illustrates the lead-lag relationship between Twitter sentiment and Bitcoin price.

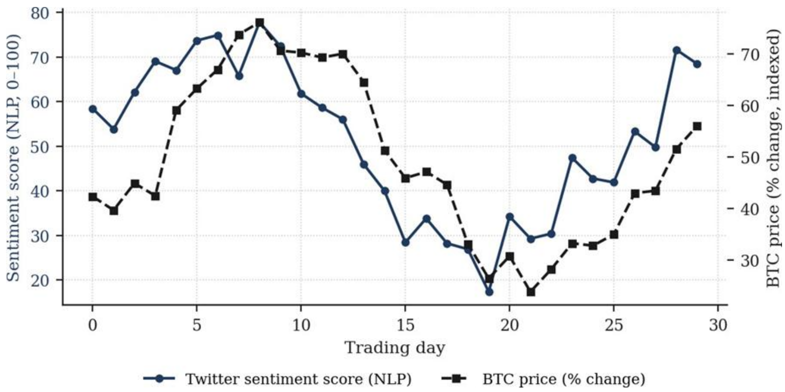

Figure 3. Twitter sentiment as a leading indicator of BTC price (stylised representation). Sentiment scores derived via NLP precede price movements by approximately 2.5 days.
Source: Author's reconstruction following Bollen et al. (2011) and Demir et al. (2024). Empirical evidence indicates directional accuracy of up to 80% at 2–3 day horizons.

Second, demographic and overconfidence profiles have been documented. UK and US studies consistently characterise the typical crypto investor as young and male, displaying significantly higher levels of overconfidence than traditional asset-class investors (Hidajat, 2019; Nareswari et al., 2021; Rijanto, 2024). The behavioural consequence is well-documented: higher trading frequency, shorter holding periods, and lower realised returns relative to comparable equity investors. Figure 4 summarises the demographic and behavioural-proxy contrasts.

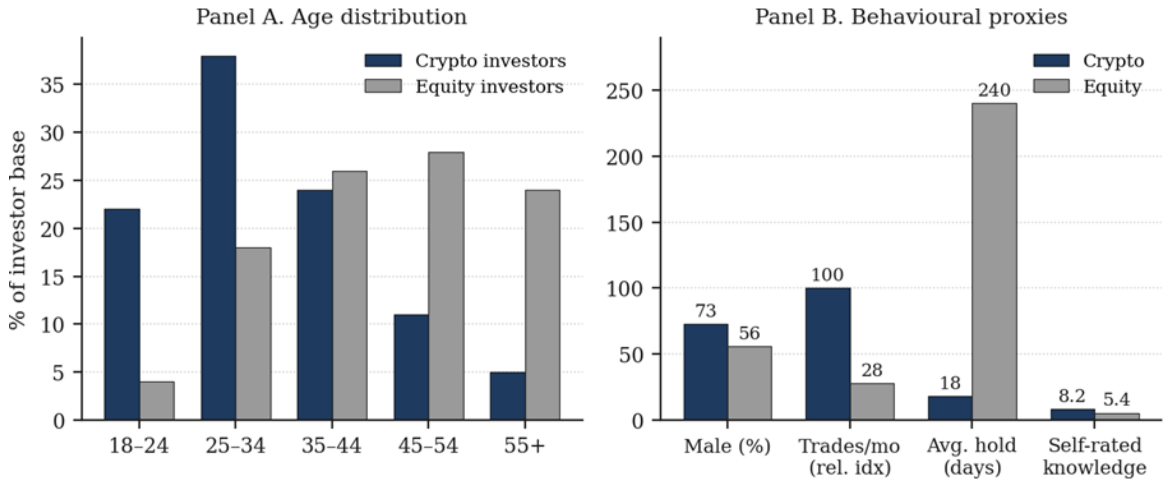

Figure 4. Demographic and behavioural-proxy profile of crypto versus equity investors. Panel A: age distribution. Panel B: behavioural proxies for overconfidence.
Source: Author's compilation from Hidajat (2019), Nareswari et al. (2021), and Rijanto (2024). Behavioural proxies are normalised; equity trading frequency is set as the reference baseline.

Third, empirical work on Decentralised Finance protocol adoption has identified a "halo effect" whereby the headline Annual Percentage Yield (APY) masks underlying risks of impermanent loss and smart-contract vulnerability (Chen & Bellavitis, 2020; Aisyah & Rahmawati, 2025). The simplification of complex risk into a single yield number creates a powerful affective heuristic in which high APY is read as quality.

Critique and Identified Gap

A genuine tension exists in the literature between *technological determinism* ("Code is Law") and *human irra-tionality*. While blockchain purists argue that automated execution will progressively render markets more efficient, the accumulating evidence suggests that human nature dominates (Seraj et al., 2022; Khan, 2023). There is also genuine debate about whether observed sentiment is "irrational" at all: when an asset has no cash flow, the only available information is price action and social-media volume, under which conditions herding may itself be a rational response to information scarcity (Hirshleifer, 2015). Despite the volume of work in this area, cross-cycle behavioural analysis remains largely absent; most studies examine a single boom or a single crash, leaving open the empirical question of whether investors learn across cycles.

III. Methodology And Research Design

Research Philosophy and Approach

The study adopts a pragmatist research philosophy, well-suited to the analysis of nascent and volatile financial ecosystems. Pragmatism transcends the inflexibilities of pure positivism and pure interpretivism, holding that the truth of digital-asset markets is a socially-constructed process whose validity is judged by its practical implications for investors and the broader economy. This basis enables the integration of heterogeneous data streams — both on-chain quantitative metrics and social-media sentiment — and asks what works in describing volatility, rather than enforcing a single financial dogma.

A deductive–inductive hybrid (abductive qualitative) approach is employed. The deductive component applies established behavioural finance theories (Kahneman & Tversky, 1979; Lo, 2004; Simon, 1955) to digital assets, anchoring the analysis in decades of peer-reviewed psychology research. The inductive component recognises that digital assets have unique architectural features — smart-contract programmability, tokenomic incentives, permanent transparency — opening space for "digital-native biases" such as Yield-Blindness and Airdrop-Anchoring.

Data Sources

The analysis is built on a rigorous secondary-data synthesis triangulating five streams of evidence. Peer-reviewed literature is drawn from a comprehensive Scopus and Web of Science search (2014–2025) on behavioural finance, cryptocurrency sentiment, digital herding, and heuristic decision-making (Kumar & Goyal, 2024; Zahera & Bansal, 2018). On-chain metrics are sourced from Glassnode, CryptoQuant, and Dune Analytics, focusing on Market Value to Realised Value (MVRV) ratios, HODL waves, and exchange flow trends as hard proxies for investor psychology (Glassnode, 2024). Sentiment datasets comprise historical NLP-derived sentiment scores from Twitter (X), Reddit, and major Discord communities drawn from peer-reviewed corpora (Bollen et al., 2011; Ranco et al., 2015). Institutional reports — including post-mortem analyses from the IMF, the Financial Stability Board, and major research firms (Chainalysis, Messari) — provide ecosystem-level evidence. Regulatory documents from the SEC, ESMA, and the EU's Markets in Crypto-Assets (MiCA) regulation map the government–behaviour interface.

Analytical Techniques

Two principal techniques transform raw data synthesis into a coherent theoretical framework. *Thematic syn-thesis*, following Braun and Clarke (2006), is applied to qualitative data, with lower-order codes iteratively grouped into higher-order categories such as "Social Influence Catalysts" and "Cognitive Anchoring Mechanics" — moving past summary toward critical interpretation of how themes interact to produce market cycles. *Conceptual modelling* is used to construct the IDABM following a System Dynamics logic in which relational causalities are drawn between variables (e.g., a rise in platform gamification reduces rational friction, which in turn raises sentiment volatility). These relationships are formalised mathematically in Section 5, providing a bridge between qualitative observation and quantitative testability.

Reliability, Validity, and Limitations

Four rigour controls are applied to meet the standards required for journal publication: *construct validity* (bias indicators are operationalised via empirical proxies — for example, overconfidence is measured by trading volume relative to market averages, not only by self-report); *internal validity* (pattern-matching is used to test whether the behavioural framework explains diverse market events including the 2017 ICO crash and the 2022 Terra/Luna collapse); *reliability* via an audit trail in which the thematic-coding process is documented; and *ex-pert triangulation* against institutional reports to confirm alignment with real-world market dynamics. Four inherent limitations are acknowledged: the sentiment proxy problem (social-media volume is vulnerable to bot noise and astroturfing); survival bias (data over-samples successful or spectacularly unsuccessful assets); innovation lag (the pace of DLT innovation may introduce variables not yet covered in the 2024–2025 literature); and data anonymity (the pseudonymity of blockchain addresses precludes granular demographic study).

IV. Analysis And Findings

The Valuation Vacuum and Heuristic Dominance

Conventional finance computes value as the present value of future cash flows. Most digital assets generate no revenues, dividends, or coupons — creating a structural *valuation vacuum* that the human mind reflexively fills with cognitive shortcuts. The absence of fundamental anchors is here interpreted as the principal driver of *heur-istic dominance* in digital-asset price formation.

The *representativeness heuristic* (Tversky & Kahneman, 1974) drives investors to evaluate new, untested assets by surface similarity to previous successes. The clearest case is meme-coin purchasing, in which buying decisions are based not on usefulness but on resemblance to Dogecoin's 2021 trajectory (Jain et al., 2023; Putra et al., 2025). *Anchoring bias* is similarly prevalent: investors anchor expectations on a token's all-time high (ATH) and perceive subsequent lower prices as a "discount", regardless of whether the original ATH was supported by any fundamental rationale (Al-Mansour, 2020). This heuristic dominance is not exclusively a retail phenomenon; institutional hype cycles demonstrate that even sophisticated funds succumb to *availability bias*, with recent publicised successes (e.g., Solana) determining capital flows and producing sectoral clustering without idiosyncratic due diligence.

The Digital FOMO–Herding Loop

Thematic synthesis of market data and social-media sentiment identifies a self-reinforcing feedback structure that is qualitatively distinct from traditional herding behaviour. Where traditional herding propagates over weeks through news structures, digital herding executes in milliseconds via social-media echo chambers and algorithmic amplification (Dedousi & Fassas, 2025; Khan, 2023). The loop comprises four psychological phases, illustrated in Figure 5.

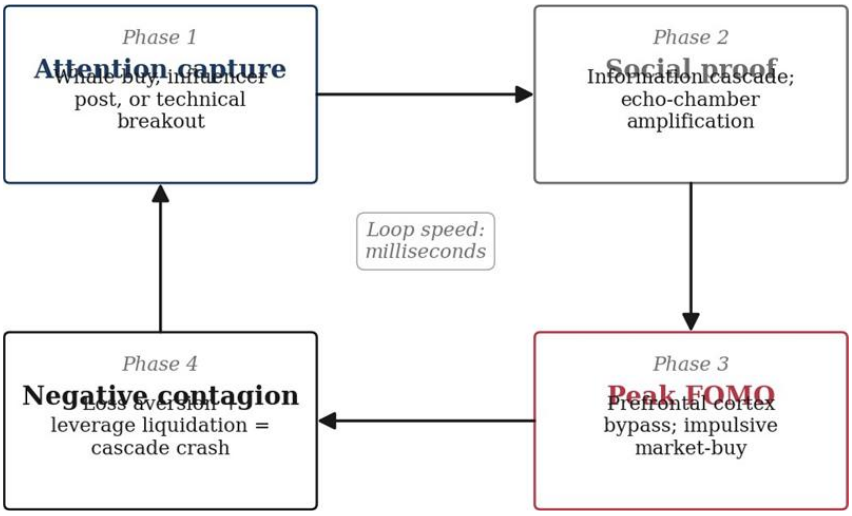

Figure 5. The Digital FOMO–Herding Loop: a four-phase psychological cycle reinforced by social-media velocity.
Source: Author's framework. Phase descriptions synthesised from Bollen et al. (2011), Ranco et al. (2015), Kumar & Goyal (2024), and Dedousi & Fassas (2025).

Phase 1 — Attention Capture: a technical breakout, a whale buy, or a celebrity-influencer endorsement initiates a price divergence visible on charts. *Phase 2 — Social Proof & Information Cascades*: as price rises, posts pro-liferate across X and Reddit. Investors observe others realising rapid profits, triggering social proof. The wisdom of crowds is misread as superior knowledge, producing an information cascade in which negative private information is suppressed in favour of the dominant positive social signal. *Phase 3 — Peak FOMO*: the fear of being left behind dominates cognition; emotional arousal bypasses the prefrontal cortex's risk-evaluation function, producing impulsive market-buy orders. *Phase 4 — Negative Emotional Contagion*: when the margin-al "greater fool" exits, even a small price decline triggers loss aversion. Automated liquidation of leveraged positions amplifies the downturn. Sentiment on social media flips from "moon" to "scam" within hours, generating a cascading sell-off whose violence often exceeds the prior advance.

Case-Based Evidence: Terra/Luna and FTX

The 2022 market collapses provide concentrated evidence of how individual behavioural biases scale to systemic crisis. The Terra/Luna collapse reveals a textbook case of *escalation of commitment*. Although math-ematicians and economists had repeatedly warned about the structural instability of the UST stablecoin peg, the "Luna Community" — self-styled "Lunatics" — increased rather than decreased their conviction (Aisyah & Rahmawati, 2025). This tribal identity functioned as a social firewall against contradictory data; when the de-pegging began, exit was psychologically blocked by the *sunk-cost fallacy*. Figure 6 maps the LUNA price and UST peg dynamics against the corresponding behavioural phases.

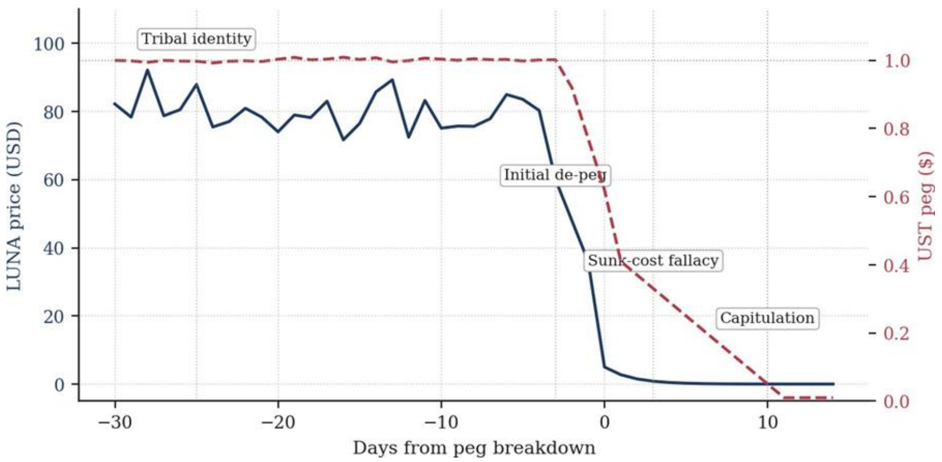

Figure 6. The Terra/Luna collapse: LUNA price (navy, left axis) and UST peg (red, right axis) plotted against days from peg breakdown, with behavioural phases annotated.
Source: Author's reconstruction from on-chain data and post-mortem reports (Glassnode, 2024).

The FTX case illustrates a complementary pattern: the *authority and halo effects*. The perceived genius of Sam Bankman-Fried, reinforced by his "effective altruism" narrative, led venture capitalists, celebrities, and retail investors alike to neglect basic corporate-governance scrutiny. This case demonstrates a profound finding: institutional due diligence often functions as *social proof in a suit* — once Sequoia Capital invests, its imprimatur halos all subsequent participants and crowds out independent risk analysis.

Bias Taxonomy by Asset Class

Different digital sub-sectors activate distinct psychological profiles; treating "crypto" as a single bias-homogeneous asset class is a category error. Figure 7 presents a cross-asset bias-prevalence matrix derived from the literature synthesis. Cryptocurrencies functioning as a store of value (Bitcoin) are dominated by *scarcity heuristics* and *narrative anchoring*; DeFi protocols are characterised by *complexity bias* and *yield-blindness*; NFTs exhibit the strongest *affect and identity* dynamics, behaving as Veblen goods in which conspicuous ownership status drives price; and meme coins concentrate FOMO, herding, and affective identification.

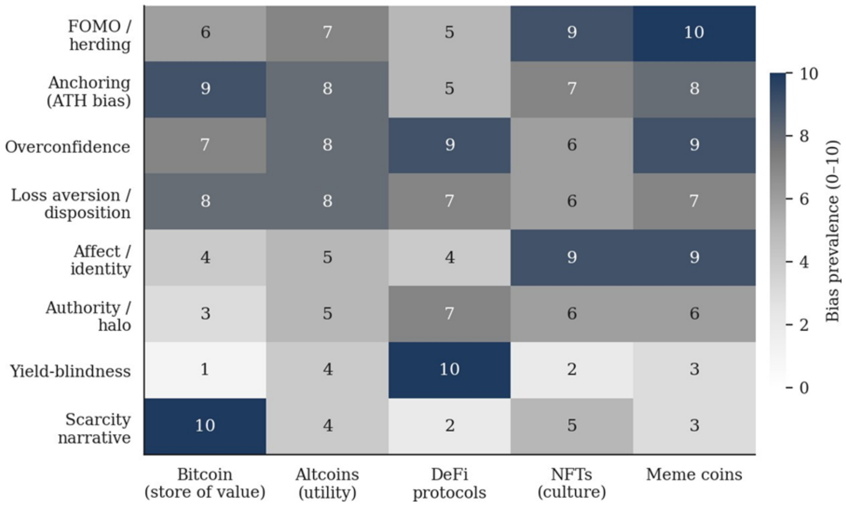

Figure 7. Behavioural bias prevalence by digital asset class (0–10 scale).
Source: Author's synthesis from Tversky & Kahneman (1974), Hidajat (2019), Putra et al. (2025), and Jain et al. (2023). Prevalence scores are interpretive.

V.The Integrated Digital Asset Behavioural Model (IDABM)

Synthesising the findings in Section 4, this paper proposes the Integrated Digital Asset Behavioural Model (IDABM). The model posits that the current price *P(t)* of a digital asset is a dynamic equilibrium of four core behavioural variables: social velocity (S_V), heuristic load (H_l), platform gamma (P_γ), and liquidity leverage (L_l). The conceptual structure is presented in Figure 8.

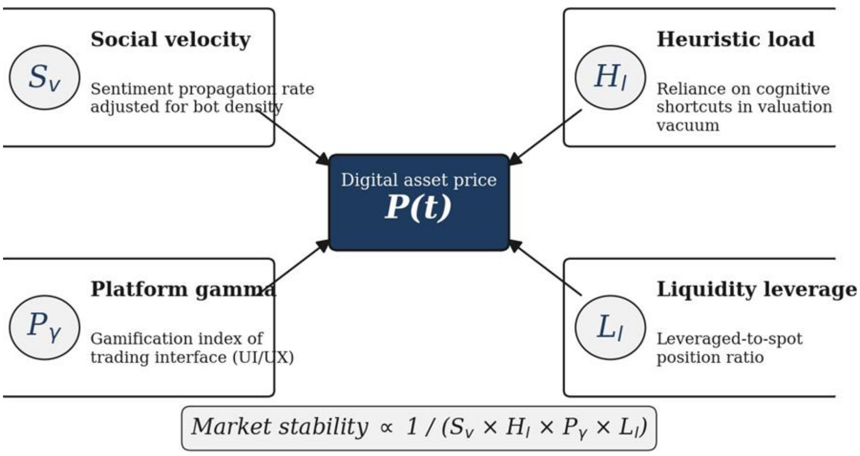

Figure 8. The Integrated Digital Asset Behavioural Model (IDABM). Four behavioural variables jointly determine digital asset price formation; market stability is inversely proportional to their product.
Source: Author's framework.

The variables are defined as follows. *Social velocity (S_v)* is the rate of sentiment propagation across social networks, adjusted for bot density; high S_v produces compressed cycle times. *Heuristic load (H_l)* is the degree to which an asset lacks fundamental valuation anchors, increasing reliance on cognitive shortcuts. *Platform gamma (P_γ)* is the gamification index of the trading interface — push notifications, simplified leverage toggles, one-tap trading — that reduces rational friction. *Liquidity leverage (L_l)* is the ratio of leveraged to spot posi-tions, which determines the velocity of any subsequent crash through liquidation cascades. The model's central proposition is expressed in Equation 1:

$$\text{Market Stability} \propto 1 / (S_v \times H_l \times P_\gamma \times L_l) \qquad (1)$$

Equation 1 implies that market stability is inversely proportional to platform gamma: as interfaces become more frictionless and gamified, heuristic load is more easily triggered, and the system converges on the fat-tail volatility characteristic of digital assets. The framework is also predictive — when S_v and L_1 are simultan-eously high while fundamental transparency is low, a sentiment bubble is mathematically probable. Figure 9 illustrates the empirical distribution of platform gamma and rational friction across contemporary trading inter-faces.

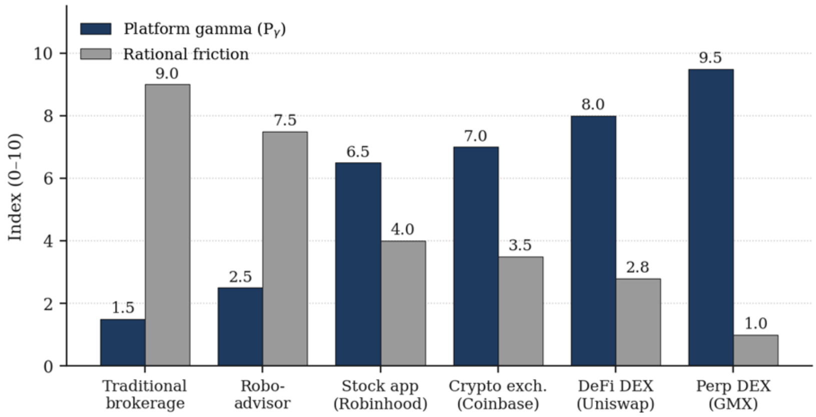

Figure 9. Platform gamma versus rational friction across trading interfaces (0–10 index).
Source: Author's compilation from product documentation and UI/UX analysis of representative platforms.

Figure 10 finally demonstrates that the recurring cycles of crypto markets — 2017 ICO bubble, 2018 crash, 2020–21 DeFi/NFT mania, 2022 Terra/Luna and FTX collapse, 2024–25 institutional wave — share a common behavioural anatomy consistent with the IDABM dynamics. This cross-cycle consistency supports the Adaptive Markets Hypothesis (Lo, 2004) interpretation of crypto as an evolving ecosystem rather than an efficient mar-ket.

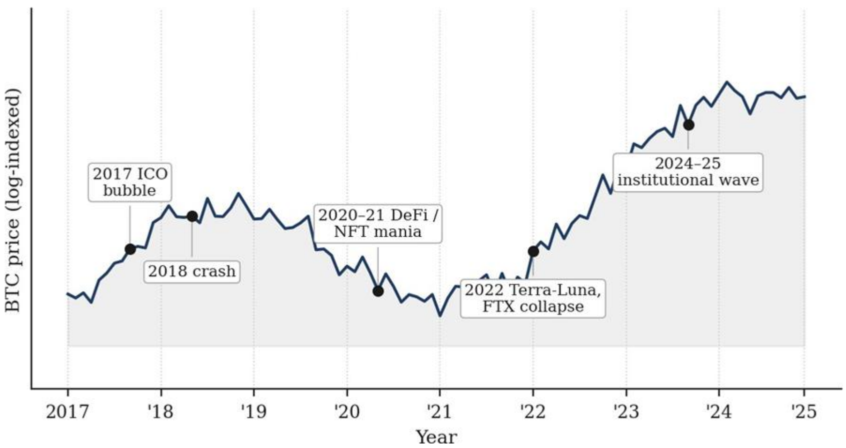

Figure 10. Recurring crypto market cycles, 2017–2025, with major behavioural events annotated.
Source: Author's stylised representation using log-indexed BTC price and major-event annotations.

VI. Discussion And Implications

Theoretical Implications

The findings in this paper constitute a substantive challenge to the strong-form Efficient Market Hypothesis (Fama, 1970). Classical EMH posits that prices instantaneously reflect all available information. In digital-asset markets, however, the "information" being processed is not objective fundamental data but the prevailing psychological state, producing a *paradox of sentiment-efficiency*: the market is efficient at expressing the current mood while remaining inefficient at expressing fundamental reality. This positions the Adaptive Markets Hypothesis (Lo, 2004) as the most appropriate primary lens for digital finance; within AMH, market participants do not act as rational optimisers but learn and evolve through trial and error. A theoretical reframing follows: volatility in this domain is not a sign of market failure but the *discovery cost* of decentral-ised systems.

Practical Implications for Investors

For portfolio managers and retail participants alike, the practical implication of the IDABM is the need for *cog-nitive hygiene*. Personal returns are routinely sacrificed on the altar of platform gamma. Concrete defences include institutional friction — programmed cooling-off delays and explicit separation of trading interfaces from social-media feeds — and bias-aware diversification. The bias taxonomy (Section 4.4) implies that crypto "diversification" is often illusory: when all portfolio assets are exposed to the same affect heuristic or narrative anchor, the portfolio is not diversified. Genuine diversification combines assets with structurally different psychological drivers.

Policy and Regulatory Implications

Current regulatory regimes — including the EU's MiCA and SEC enforcement actions — focus principally on informational symmetry through risk disclosures, whitepapers, and audits. Necessary as these are, the analysis here suggests that, in markets characterised by bounded rationality, disclosure alone is insufficient: technical documents are not processed by the populations most exposed to risk (Soomro et al., 2024). Policy must shift toward *behavioural guardrails*. Three recommendations follow. First, *algorithmic accountability*: regulators should require social-media platforms to disclose the recommendation engines that drive financially-relevant FOMO. Second, *UI/UX ethics*: gamified trading apps should be regulated as a category, with practices borrowed from gambling (confetti animations, aggressive push notifications, simplified high-leverage toggles) classified as predatory design and either restricted or required to carry friction-imposing safeguards. Third, *be-havioural literacy*: financial education must shift focus from "how to trade" to "how cognition fails when trading", with regulator-mandated heuristic warnings during periods of high volatility functioning as digital circuit-breakers.

Limitations and Future Research

Three limitations require acknowledgement. First, the *sentiment anonymity problem*: aggregate social-media volume can be measured, but the share of organic retail sentiment versus coordinated bot astroturfing cannot reliably be disentangled, leaving the S_V variable in the IDABM partially a black box. Second, *survival bias*: ex-amined cases (FTX, Terra/Luna) are catastrophic by selection; quieter cases of rational adoption are systematically under-sampled. Third, *cross-cultural variability*: psychological responses to volatility differ across regions (Statman, 2008), and a universal IDABM would incorporate cross-cultural weighting factors reflecting distinct socio-economic reference points. Four research priorities follow: (a) algorithmic sentiment analysis distinguishing organic human emotion from LLM-generated artificial sentiment; (b) neuroscientific validation through fMRI or EEG measurement of dopaminergic activity during flash-crash events; (c) longitudinal studies of institutional learning across cycles; and (d) cross-cultural behavioural audits of digital-asset adoption.

VII. Conclusion

This study has demonstrated that digital-asset volatility is fundamentally a psychological and socio-technical phenomenon, not an economic one. Three principal findings emerge. First, the absence of conventional cash-flow anchors — the valuation vacuum — drives investors into a regime of heuristic dominance, in which price discovery proceeds via narrative anchoring and the representativeness heuristic. Second, herding and FOMO are not merely present in digital-asset markets but are *structurally enhanced* by the platform gamma of contem-porary trading interfaces. Third, the cyclical theory of behavioural risk is empirically supported: FTX, Terra/ Luna, and the recurring boom-bust cycles share a common behavioural anatomy. Digital assets thus emerge as the world's first *pure-sentiment market*, in which technological visibility is consistently undermined by behavioural opacity, and fat-tailed volatility is the structural norm rather than the exception. The principal contribution of this research, the Integrated Digital Asset Behavioural Model

(IDABM), provides a novel multi-variable framework formalising relationships between social velocity, heuristic load, platform gamma, and liquidity leverage. Where traditional models treat investor bias as an independent factor, the IDABM acknowledges that bias is *multiplied* by the technological environment in which it operates. By incorporating Platform Gamma as an explicit variable, the study bridges financial economics and Human–Computer Interaction (HCI), giving future researchers a method to measure how gamified UI/UX design affects market stability.

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