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Digital Information Asymmetry and Investment Decision-Making in the Mutual Fund Industry

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Abstract
The rise of digital financial influencers — commonly called "finfluencers" — on platforms such as YouTube, Instagram, and Telegram has changed how ordinary retail investors learn about mutual funds. Historically, this was an area where information was concentrated in the hands of a few actors: certified financial advisors, asset management companies (AMCs), and formal regulatory disclosures. Retail investors had comparatively little independent access to reliable information, a condition economists call information asymmetry. Social media has inserted a new, informal layer of information between these traditional sources and the investor, and this study investigates what that layer actually does: does it help close the information gap, or does it introduce a different kind of imbalance built on oversimplified, biased, or commercially motivated content?
The study is grounded in three theoretical traditions — Information Asymmetry Theory, Source Credibility Theory, and the Theory of Planned Behaviour — which together explain, respectively, why the information gap exists, why some influencers are trusted more than others, and how perceptions translate into actual investing behaviour. Using a structured questionnaire administered to retail mutual fund investors, the study applies regression analysis and Structural Equation Modelling (SEM) to test how exposure to influencer content shapes investors' sense of being adequately informed, their trust and confidence, and ultimately, three measurable outcomes: which funds they choose, how diversified their portfolios are, and whether they keep their Systematic Investment Plans (SIPs) running consistently over time.
The design also tests whether the strength of these effects depends on who the investor is — their age, income, existing financial literacy, and prior investing experience — and it incorporates investor awareness of SEBI's 2023–2025 finfluencer regulations as a further factor shaping trust in influencer-sourced information. The expected contribution is a clearer, evidence-based answer to whether finfluencers function as genuine intermediaries that narrow the information gap for retail investors, or whether they merely relocate the asymmetry problem rather than solving it — with direct implications for regulators, AMCs, and investor-education programmes.

Keywords: finfluencers, information asymmetry, mutual funds, retail investors, SEBI, investment decision-making, structural equation modelling (SEM)

1. Introduction Why This Question Matters

Mutual fund investing has traditionally required investors to interpret dense, technical documents — scheme information documents, expense ratios, risk-o-meters, portfolio disclosures — that are written for regulatory compliance rather than for a layperson's understanding. In principle, certified financial advisors exist to bridge this gap. In practice, a large and fast-growing share of India's retail investors, especially younger and first-time investors, now form their first impressions of mutual funds not from an advisor or an AMC brochure, but from a short video, an Instagram reel, or a Telegram post created by an independent content creator with no formal advisory obligation to the viewer.

This shift matters because it changes who controls the flow of information in a market that was built around a small number of regulated, accountable information gatekeepers. A finfluencer may genuinely simplify a complicated topic and make it accessible — or they may simplify it in a way that omits risk, exaggerates returns, or is shaped by an undisclosed commercial relationship with a distributor or platform. Distinguishing between these two possibilities, at scale and with data rather than anecdote, is the underlying motivation for this research.

2. Theoretical Framework

The study is built on three theories that, together, form a chain of reasoning from "why is there an information problem" through "why would anyone trust an influencer to fix it" to "how does that trust actually change behaviour." Understanding each theory separately makes the hypotheses in Section 4 much easier to follow.

2.1 Information Asymmetry Theory

Information Asymmetry Theory originates in classical economics and describes situations where one party in a transaction knows meaningfully more than the other. In financial markets, this typically means the seller or manager of a product understands its risks, costs, and likely performance far better than the buyer does. Applied to mutual funds, the asset management company and its distributors are the "informed" party, while the retail investor is the relatively "uninformed" party. This gap can lead to adverse selection (investors picking unsuitable products because they cannot properly evaluate the alternatives) or to a general erosion of trust in the market. The theory gives this study its central problem: does an investor feel they know enough to make a sound decision, and where does that feeling of "knowing enough" come from?

2.2 Source Credibility Theory

Source Credibility Theory, drawn from communication and marketing research, explains why people are more persuaded by some sources of information than others. It identifies factors such as perceived expertise, trustworthiness, and attractiveness as the drivers of a source's persuasive power. In the context of this study, it explains why a finfluencer with a large following, a confident on-camera presence, and an appearance of financial expertise can shift investor beliefs even without any formal certification or regulatory accountability. This theory is what connects "exposure to an influencer" to "perceived credibility of that influencer" — a distinction that matters because simply watching content is not the same as trusting it.

2.3 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour explains how attitudes and perceptions translate into actual, observable behaviour rather than remaining just opinions. TPB proposes that behaviour is shaped by three things: a person's attitude toward the behaviour (do they see investing in a particular fund positively?), subjective norms (do people around them, including influencers they follow, seem to endorse it?), and perceived behavioural control (do they feel capable of making the decision themselves?). This theory supplies the final link in the study's logic: it explains how a reduction — or persistence — in perceived information asymmetry actually shows up in real investment choices, such as which fund is selected, how diversified the portfolio becomes, and whether an SIP continues or is abandoned.

2.4 How the Three Theories Fit Together

Read together, the three theories describe a single causal chain that this study sets out to test empirically: Information Asymmetry Theory identifies the underlying knowledge gap; Source Credibility Theory explains how an influencer earns enough trust to plausibly fill that gap; and the Theory of Planned Behaviour explains how the resulting change in perceived information — whether it genuinely narrows the gap or not — ultimately shapes real investment behaviour. The study's core mediating variable, perceived information asymmetry, sits at the pivot point of this chain.

3. Research Objectives

The six objectives below move from description (how much do investors rely on influencers?) to explanation (what effect does that reliance have, and through what mechanism?) to context (does this vary by investor type, and does regulation change the picture?).

1. To examine the extent to which retail investors rely on digital influencers as a source of mutual fund-related information, relative to traditional sources (advisors, AMC disclosures, official websites).
2. To assess the effect of digital influencer exposure and perceived credibility on investors' perceived information asymmetry regarding mutual fund products.
3. To analyze the relationship between reduced or persisted information asymmetry and the quality of investment decision-making (fund selection confidence, diversification behaviour, SIP continuity).
4. To examine the mediating role of information asymmetry between digital influencer exposure and investment decision outcomes.
5. To investigate the moderating effects of demographic variables (age, income, financial literacy, investment experience) on the influencer–decision-making relationship.
6. To evaluate investor awareness of, and attitudes toward, SEBI's regulatory framework on finfluencers, and its perceived effect on trust and information reliability.

Objectives 1–3 establish the basic descriptive-to-causal chain (exposure → asymmetry → decision quality). Objective 4 formally tests whether information asymmetry is the mechanism carrying that effect, rather than just a coincidental correlation. Objectives 5 and 6 ask whether this chain works the same way for everyone, or whether it bends depending on who the investor is and what they know about the regulatory environment.

4. Hypotheses

Each hypothesis below is stated formally, followed by a plain-language explanation of the reasoning behind it. The hypotheses are deliberately framed to be falsifiable: the study does not assume influencers are beneficial or harmful in advance — that is the open empirical question being tested.

H1

Exposure to digital influencer content is positively associated with retail investors' engagement in mutual fund investment activity.

In plain terms: the more finfluencer content someone consumes, the more actively they are expected to participate in mutual fund investing — for example, starting new SIPs, exploring new funds, or investing more frequently.

H2

Perceived credibility of digital influencers is positively associated with reduced perceived information asymmetry among retail investors.

In plain terms: it is not exposure alone that matters, but whether the investor actually believes the influencer is credible. Believing an influencer is trustworthy is what makes an investor feel more informed — mere exposure without trust may not have the same effect.

H3

Reduced perceived information asymmetry is positively associated with the quality of mutual fund investment decision-making (confidence, satisfaction, lower post-investment regret).

In plain terms: feeling better informed is expected to translate into better decision outcomes — more confidence, more satisfaction, and less regret after the fact.

H4

Information asymmetry significantly mediates the relationship between digital influencer exposure and investment decision-making quality.

In plain terms: this hypothesis tests whether information asymmetry is the actual mechanism connecting influencer exposure to decision quality, rather than the two simply happening to move together. Statistically, this is tested as a mediation path: exposure → asymmetry → decision quality.

H5

Financial literacy moderates the relationship between digital influencer exposure and perceived information asymmetry, such that the effect is weaker for investors with higher financial literacy.

In plain terms: influencer content is expected to matter less for people who already understand finance well, since they have less of a gap for an influencer to fill in the first place.

H6

Age and investment experience moderate the relationship between digital influencer credibility and investment decision-making quality.

In plain terms: the same perceived credibility of an influencer may translate into different decision outcomes depending on how old or experienced the investor is — for instance, a young first-time investor may act on influencer credibility more directly than a seasoned investor would.

H7

Awareness of SEBI's finfluencer regulations is positively associated with investors' trust in digital influencer-sourced information.

In plain terms: knowing that regulations exist — and that some influencers comply with them — is expected to make investors trust influencer content more, since regulation functions as a signal of accountability.

5. Literature Review

5.1 Introduction to the Literature Landscape

Research relevant to this study draws from four broad streams: (i) the economics literature on information asymmetry in financial markets, (ii) the emerging behavioural finance and marketing literature on finfluencers, (iii) studies on social-media-driven biases — herding, overconfidence, and fear of missing out (FOMO) — among retail investors, and (iv) the regulatory and legal literature on India's evolving finfluencer framework. Each stream is reviewed below, followed by an identification of the specific gap this study addresses.

5.2 Information Asymmetry in Mutual Fund Markets

The theoretical foundation for information asymmetry in this study traces back to classical information economics, where a gap exists between informed and uninformed parties in a market, potentially leading to adverse selection or moral hazard. Applied to mutual funds, scholars frame fund managers and distributors as the informed party and retail investors as the relatively uninformed party. Some researchers model the price-setting strategies between fund providers and investors to explain how active fund markets persist despite this asymmetric information, while others note that the predictive value of a fund's past performance for its future returns remains contested — with more recent work tending to favour the view that past performance carries limited predictive power.

Other strands look beyond fund selection toward fund flows and disclosure. Work on retail fund inflows and switch-outs has linked correlated trading patterns to information asymmetry between incoming investors and existing unit-holders, particularly where funds are distributed through intermediaries. Separately, research on sustainability-themed (ESG) mutual funds has used disclosure documents to show that information asymmetry between fund companies and investors persists even where formal regulatory disclosure requirements exist — suggesting that disclosure rules alone do not fully close the gap. A further strand applies portfolio-choice theory under asymmetric information directly to the puzzle of why individual investors continue to purchase actively managed funds despite mixed evidence on manager skill.

Collectively, this literature establishes information asymmetry as a structural, persistent feature of the mutual fund market rather than a temporary or easily-solved problem, and it frames the issue primarily at the level of disclosure design and the manager–investor relationship. What is largely missing from this literature is an account of how an intermediate, informal layer of information — principally digital influencers — alters this asymmetry from the investor's side. This is precisely the gap the present study is positioned to address.

5.3 Finfluencers and Retail Investment Decisions

A growing and recent body of work addresses financial influencers directly. One framework grounded in the Theory of Planned Behaviour found that finfluencers significantly structure retail investors' decision-making process through their perceived expertise, attitudes, and influence over perceived behavioural control, while also noting that the advice received can differ systematically by investor gender. A companion strand frames finfluencers as occupying a dual role: they can improve financial literacy and democratize access to investment knowledge, but can equally amplify speculative behaviour, encourage herding, or spread unverified information — with younger and less experienced investors identified as the primary audience at risk.

Work using structural equation modelling has examined the underlying psychological mechanism more precisely, finding that the perceived authority of a finfluencer has a strong direct effect on retail investment choices, and that this relationship operates substantially through social media trust as a mediating variable — trust is the channel through which digital influence is converted into actual investing behaviour. This is a particularly relevant precedent for the present study's own mediation logic, even though the present study substitutes information asymmetry for social media trust as the mediating construct — a deliberate shift explained further in Section 5.6.

The strongest causal evidence to date comes from a Nordic study using a decade of daily trading data and a design in which followers were randomly assigned to specific finfluencers, allowing researchers to isolate a genuine causal effect rather than a mere correlation. That study found finfluencers have a sizeable impact on followers' portfolio and trading decisions, with effects stronger for influencers commanding large followings, holding central positions within follower networks, or engaging frequently in discussion — and the effects were amplified among women and among investors who follow comparatively few accounts. A parallel regulatory study in Canada similarly found, experimentally, that finfluencer recommendations significantly shift retail trading decisions, while cautioning that the relationship is not inherently harmful unless the underlying advice is of low quality or is driven by undisclosed commercial incentives.

5.4 Social Media, Behavioural Biases, and the Indian Retail Investing Boom

A separate but overlapping literature documents the broader behavioural consequences of India's digital investing boom, driven substantially by the rise of low-cost trading and investment apps. Several Indian studies note that the ease of access offered by these platforms has coincided with a documented rise in demat accounts, with retail investors now accounting for a much larger share of market turnover than several years prior, and a large proportion of this growth coming from young, first-time, and non-metro investors with comparatively limited formal financial education.

Indian studies focused on Tier-1 city investors have found evidence of strong herding behaviour during periods of market volatility, with social media and group-based investment forums identified as significant contributing channels — a pattern particularly pronounced among inexperienced investors influenced by perceived market sentiment and peer discussion on platforms such as WhatsApp and Telegram. Related survey-based research connects investors' emotional intelligence to biases including herding, overconfidence, and the disposition effect (the tendency to hold losing investments too long while selling winners too early), and links these biases specifically to mutual fund portfolio churning frequency — providing one of the few direct empirical bridges between social and behavioural drivers on one hand, and mutual fund-specific outcomes on the other. More recent reviews reinforce that social media materially amplifies investor psychology and behavioural biases, while pointing toward financial literacy and structured investor education as the most commonly recommended mitigating mechanism.

5.5 The Indian Regulatory Response: SEBI and Finfluencers

A final and fast-moving strand of literature — largely legal and policy-oriented rather than empirical — traces India's regulatory response to the finfluencer phenomenon. The Securities and Exchange Board of India's (SEBI) engagement began with a 2023 consultation paper addressing the association between SEBI-registered intermediaries and unregistered entities, including finfluencers, and proposing obligations around registration, disclosure, and penalties for misleading claims. This was followed by board-level approval of related proposals in mid-2024, an October 2024 circular restricting associations between regulated entities and unregistered influencers, and a further circular effective from January 2025 that restricts financial educators from using live or near-live stock price data, permitting only data lagged by three months — a measure intended to prevent real-time trading tips from being disguised as educational content.

Commentators note that SEBI's framework explicitly extends these association restrictions to mutual fund distributors and sub-brokers, not merely equity brokers, directly implicating the mutual fund distribution channel central to the present study. Legal scholars have also highlighted enforcement gaps, including the practice of unregistered finfluencers renting SEBI registration numbers from registered investment advisers to create a false appearance of compliance — a reminder that formal regulation and investor-perceived trustworthiness do not always move together.

5.6 Synthesis and Research Gap

Three observations emerge from this review. First, the information asymmetry literature is theoretically well developed but has been applied almost exclusively to manager–investor or disclosure-level relationships, rarely incorporating the influencer layer that now mediates how many retail investors first encounter mutual fund information. Second, the finfluencer literature is empirically active and increasingly rigorous, but is concentrated on equities and general trading behaviour rather than mutual funds specifically, and tends to model trust — rather than information asymmetry — as the mediating mechanism. Third, the Indian behavioural-finance literature documents the consequences of social-media-driven biases broadly, but rarely isolates mutual fund decision quality as a distinct outcome variable, and the regulatory literature on SEBI's finfluencer framework remains largely descriptive rather than tested against actual investor perception or behaviour.

This study addresses these gaps by combining the information asymmetry framework with finfluencer-specific constructs in a mutual fund context, treating information asymmetry — rather than trust alone — as the mediating mechanism, and incorporating awareness of SEBI's regulatory framework as a moderating variable. As of mid-2026, this specific combination has not yet been empirically tested in the available literature.

6. Research Methodology

This section explains not just what the study will do, but why each methodological choice was made — since the reasoning behind a research design is often as important to understanding the study as the design itself.

6.1 Research Design

This study adopts a quantitative, cross-sectional, survey-based research design, consistent with prior finfluencer studies that used Structural Equation Modelling (SEM) to test mediated relationships between influencer-related constructs and investment behaviour. "Cross-sectional" means data is collected from respondents at a single point in time, rather than following the same people over months or years. The study is explanatory rather than purely descriptive: it sets out to test pre-specified hypotheses derived from the conceptual framework in Section 2, rather than simply summarising patterns after the fact.

6.2 Population and Sampling

Target population: Retail individual investors in India who currently invest, or have previously invested, in mutual funds (direct or regular plans), including both SIP and lump-sum investors.

Sampling technique: Because there is no complete, accessible list of every retail mutual fund investor in India, a true random sample is not feasible. The study instead recommends a non-probability purposive/snowball sampling technique, distributed through investment-app user communities, finance-focused social media groups, and AMC/distributor networks. Where feasible, a quota-based approach — stratifying respondents by age band and city tier (metro/Tier-1/Tier-2) — is preferable to pure convenience sampling, since it helps the final sample better resemble the broader investor population even without full randomisation.

Sample size: For PLS-SEM analysis, sample size can be estimated using the "10 times rule" (roughly ten respondents for every path pointing at the most complex construct in the model) or more rigorously via power-analysis software such as G*Power. The field convention for a model of this complexity is a minimum of 200–250 valid responses, rising to 300 or more if subgroup or multi-group moderation analysis is planned.

Inclusion criteria: Respondents must be 18 years or older; must have invested in at least one mutual fund scheme; and must have some exposure to digital or social media financial content.

6.3 Data Collection Instrument

The structured questionnaire (Sections A–H, reproduced in full in Appendix A) is the primary data collection instrument, administered as a self-administered online survey to maximise reach and to minimise interviewer bias — since a live interviewer can unintentionally influence how a respondent answers. All substantive constructs use a 5-point Likert scale (Strongly Disagree to Strongly Agree), which allows the resulting data to be analysed using parametric statistical methods compatible with SEM. A pilot study with 30–40 respondents is recommended before full deployment, to check that survey items are clearly understood and that each construct shows acceptable preliminary reliability (Cronbach's alpha of at least 0.70).

6.4 Variables and Operationalization

The table below translates each theoretical construct into something that can actually be measured. "Operationalization" is the process of turning an abstract idea (such as "perceived information asymmetry") into specific, answerable survey questions.

Construct	Role	Indicators	Measurement
Digital influencer exposure & credibility (DI)	Independent	DI1–DI6	5-pt Likert, reflective
Perceived information asymmetry (IA)	Mediator	IA1–IA6 (IA1, IA5 reverse-coded)	5-pt Likert, reflective
Investment decision-making quality (DQ)	Dependent	DQ1–DQ6	5-pt Likert, reflective
Financial literacy (FL)	Moderator	FL1–FL3 + FL4 (knowledge check)	Likert + binary score
Age / investment experience	Moderator	A2, A5, EX1	Categorical / ordinal
SEBI regulation awareness (SR)	Moderator	SR1–SR4	5-pt Likert, reflective

Two of the items in the information asymmetry section — IA1 and IA5 — are worded in the opposite direction to the rest of the scale (e.g. "I feel I have access to sufficient information..." rather than "I do not have enough information..."). These are called reverse-coded items, and their numerical scores are flipped during data cleaning before being combined with the other items. This is a standard technique used to catch respondents who are answering carelessly or in a fixed pattern without actually reading each item.

6.5 Analytical Approach: Why Structural Equation Modelling (SEM)?

Structural Equation Modelling is selected over simple multiple regression because the conceptual model specifies several interrelated latent constructs (concepts, like "credibility" or "information asymmetry", that cannot be measured directly and are instead inferred from multiple survey items), a mediation path running from digital influencer exposure through information asymmetry to decision quality, and several moderators acting on different parts of that path at once. Ordinary regression can really only test one such relationship at a time and cannot properly account for measurement error in the underlying constructs. SEM, by contrast, allows the measurement model (how well the survey items represent each construct) and the structural model (how the constructs relate to one another) to be estimated simultaneously, within a single statistical framework, while correcting for that measurement error.

Within SEM, there are two broad families of estimation: Partial Least Squares SEM (PLS-SEM) and Covariance-Based SEM (CB-SEM). Given a moderately complex model, multiple moderators, some newly-adapted scale items, and a likely sample size in the 200–300 range, PLS-SEM (implemented, for example, in SmartPLS) is recommended over CB-SEM (implemented, for example, in AMOS). This is because PLS-SEM performs more robustly with smaller-to-moderate sample sizes and does not require the data to strictly follow a multivariate normal distribution, which real-world survey data often does not. CB-SEM remains a defensible alternative if the eventual sample size exceeds approximately 400 responses.

6.6 Step-by-Step Analytical Procedure

1. Data screening: remove incomplete responses, check for straight-lining (respondents selecting the same answer repeatedly without engaging with each item), and screen for statistical outliers.
2. Descriptive statistics: summarise the demographic profile of respondents, platform usage patterns, and construct-level means and standard deviations.
3. Common method bias check: use Harman's single-factor test or a full collinearity VIF approach to check that the observed relationships are not simply an artefact of collecting all data through a single survey instrument.
4. Measurement model assessment: confirm each survey item loads strongly (≥ 0.70) onto its intended construct; check Cronbach's alpha and Composite Reliability (≥ 0.70) and Average Variance Extracted (≥ 0.50); confirm discriminant validity via the HTMT ratio (< 0.85), which checks that supposedly distinct constructs are in fact measuring different things.
5. Structural model assessment: check variance inflation factors ($VIF < 5$) to rule out multicollinearity; estimate path coefficients using bootstrapping (5,000 resamples, significance threshold $p < 0.05$); assess explanatory power (R^2), effect sizes (f^2), and predictive relevance (Q^2 via blindfolding).
6. Mediation analysis (testing H4): estimate the bootstrapped indirect effect of influencer exposure on decision quality through information asymmetry, using bias-corrected confidence intervals, and assess whether the mediation is full (the direct effect disappears once the mediator is included) or partial (some direct effect remains).
7. Moderation analysis (testing H5, H6, H7): use a product-indicator or two-stage approach to estimate interaction effects, and multi-group analysis (MGA) to compare the model across age or experience subgroups.
8. Robustness checks: re-run key paths while statistically controlling for income and education, and compare results between SIP-only and lump-sum investor subgroups to check the findings are not driven by one investor type alone.

6.7 Hypotheses-to-Test Mapping

Hypothesis	Path Tested	Statistical Test
H1	DI → engagement / investment activity	Path coefficient, bootstrapping
H2	DI → IA	Path coefficient, bootstrapping
H3	IA → DQ	Path coefficient, bootstrapping
H4	DI → IA → DQ (mediation)	Bootstrapped indirect effect, bias-corrected CI
H5	FL moderates DI → IA	Interaction term (DI × FL) → IA

H6	Age / experience moderates IA → DQ	Interaction term or multi-group analysis
H7	SR → trust in influencer-sourced information	Path coefficient, bootstrapping

6.8 Software and Tools
SmartPLS 4 (or R using the seminr or plspm packages) is recommended for PLS-SEM estimation; SPSS or R for preliminary descriptive statistics, reliability analysis, and common method bias testing; and G*Power for a priori sample size and statistical power calculation.

6.9 Ethical Considerations
Informed consent will be obtained at the start of the survey; participation will be voluntary and anonymous; no personally identifiable financial account information will be collected; and respondents will be clearly informed that the study is for academic research purposes only and does not constitute investment advice.

6.10 Limitations
Three limitations are worth stating openly. First, self-reported Likert-scale data is subject to social desirability bias — respondents may answer in ways that make them look more informed or rational than they actually are. Second, a cross-sectional design (data collected at one point in time) cannot establish strict causal direction the way a longitudinal or experimental design could; the relationships tested are best understood as strong associations consistent with a causal story, not definitive proof of causation. Third, non-probability sampling limits how confidently the findings can be generalised to the broader Indian retail mutual fund investor population, so results should be framed as indicative rather than nationally representative unless probability sampling is later achieved.

7. Expected Contributions and Practical Implications
If the hypotheses are supported, the study would provide the first direct empirical test of information asymmetry — rather than trust alone — as the mechanism connecting finfluencer exposure to mutual fund decision quality, filling a gap identified clearly in Section 5.6. Beyond its academic contribution, the findings are intended to have three practical audiences:

1. Regulators (SEBI and allied bodies): evidence on whether awareness of existing finfluencer regulations actually improves investor trust and outcomes, which can inform whether current disclosure and registration rules are achieving their intended effect or need to be strengthened.
2. Asset Management Companies (AMCs) and distributors: insight into whether their own official channels are being displaced by informal influencer content, and where investors feel the biggest remaining information gaps — which could shape how AMCs design their own investor-facing communication.

Investor-education bodies: evidence on which investor segments (by age, literacy, or experience) are most affected by influencer content, allowing education efforts to be targeted more precisely rather than applied uniformly.

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