# Role of Information Sources in Shaping Mutual Fund Investment Decisions of Retail Investors: Financial Advisors / Mutual Fund Distributors (MFDs) vs Digital Platforms

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**Abstract:**

- ***Purpose:***

**This study examines the role of information sources — specifically Financial Advisors and Mutual Fund Distributors (MFDs) as against digital platforms — in shaping the mutual fund investment decisions of retail investors in Uttar Pradesh and Uttarakhand. It further asks how demographic characteristics moderate the preference for one channel over the other, and whether the choice of information source materially affects the quality of investment decisions and the type of fund selected.**

- ***Design/Methodology/Approach:***

**Primary data were gathered from 387 retail mutual fund investors across fourteen cities in Uttar Pradesh and Uttarakhand using a structured questionnaire and stratified random sampling. Descriptive statistics, Chi-square tests, one-way ANOVA and multiple linear regression were applied in IBM SPSS 26.0. The questionnaire captured the primary information source, investment decision quality, trust in that source, financial literacy and fund-type preference.**

- ***Findings:***

**Financial Advisors and MFDs remain the leading information source for 38.5% of retail investors, with digital platforms close behind at 35.1%. MFD-guided investors record higher investment decision quality (mean = 3.91) than platform users (mean = 3.54). The association between information source and fund-type preference is significant (Chi-square = 28.43, $p = 0.005$). In the regression, MFD engagement ($\beta = 0.34$, $p < 0.001$) and digital-platform use ($\beta = 0.19$, $p = 0.023$) both predict decision quality after financial literacy and income are controlled for.**

- ***Originality/Value:***

**This is among the first region-specific studies to compare human advisory channels with digital platforms in shaping mutual fund decisions among retail investors in UP and Uttarakhand. The findings carry practical value for MFDs, Asset Management Companies (AMCs), SEBI and the designers of investor-education programmes working in these markets.**

**Keywords:** *Mutual Fund Investment, Information Sources, MFD, Digital Platforms, Retail Investors, Uttar Pradesh, Uttarakhand, Investment Decision Quality, Financial Advisors.*

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## I. INTRODUCTION

The Indian mutual fund industry has grown at a remarkable pace over the last decade. By early 2025 the industry's Assets Under Management (AUM) had crossed INR 65 trillion, according to figures published by the Association of Mutual Funds in India (AMFI). Much of this expansion has come not from the metros but from the steady spread of mutual fund products into smaller towns and cities, and states such as Uttar Pradesh (UP) and Uttarakhand sit at the centre of that story. Together the two states are home to more than 240 million people, yet their mutual fund

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penetration still trails the B30 (Beyond Top 30 cities) average by a wide margin. The gap points to a large investor base that remains largely untapped.

At the heart of activating this base is a simple but consequential question: how do retail investors in these regions first hear about mutual funds, weigh them, and finally choose one? The information environment facing a first-generation investor in Lucknow or Haridwar looks very different from the one available to a seasoned investor in Mumbai or Delhi. Two broad channels dominate. The first is the traditional human advisory network — Mutual Fund Distributors (MFDs), Registered Investment Advisers (RIAs), bank relationship managers and financial planners. The second is a fast-growing digital ecosystem of fintech apps such as Groww, Kuvera, Zerodha Coin and Paytm Money, along with YouTube financial educators, AMC websites and social-media communities.

Understanding which of these channels guides investor decisions in UP and Uttarakhand, and which one leads to better outcomes, matters to several audiences at once. For AMCs it shapes how salesforce effort and digital-marketing budgets are allocated. For SEBI and the Ministry of Finance it informs investor-education policy. And for MFDs themselves it defines the competitive case for personalised advice against algorithmically curated platforms.

Despite these stakes, the academic literature on this specific comparison — MFD or financial advisor versus digital platform — within a UP and Uttarakhand retail setting is thin. Most existing studies either analyse mutual fund selection at the national level or treat digital adoption broadly, without separating investment outcomes by information source. The present paper addresses that gap using original survey evidence from 387 retail investors across fourteen cities in the two states.

The remainder of the paper is organised as follows. Section 2 states the objectives, Section 3 the hypotheses, and Section 4 reviews the relevant literature. Section 5 sets out the methodology, Section 6 reports the results, and Section 7 discusses them against prior work. Section 8 concludes with managerial implications, limitations and directions for future research.

➢ *Objectives of the Study*

The study pursues five specific objectives:

- To identify the primary information sources that retail investors in Uttar Pradesh and Uttarakhand rely on when making mutual fund investment decisions.
- To examine whether the choice of information source is significantly associated with the type of mutual fund scheme preferred.
- To compare investment decision quality scores across information-source groups (MFD versus digital platform versus others).
- To determine how demographic variables — particularly education, income, age and occupation — influence the choice of information source.
- To assess the relative contribution of MFD engagement and digital-platform use in predicting investment decision quality, after controlling for financial literacy.

➢ *Research Hypotheses*

Drawing on the objectives and the literature reviewed below, four null hypotheses were framed:

- H01: There is no significant association between the primary information source and the type of mutual fund scheme preferred by retail investors.
- H02: There is no significant difference in investment decision quality scores across information-source groups.
- H03: Demographic variables (education, income, age) do not significantly influence the choice of information source.
- H04: MFD engagement and digital-platform use do not significantly predict investment decision quality after controlling for financial literacy.

## II. REVIEW OF LITERATURE

➢ *The Role of Financial Advisors in Investment Decision-Making*

A large body of work has documented the central place of financial advisors in retail investment decisions. Calcagno, Giofre and Urzua-Infante (2017) showed that investors who consult professional advisors tend to hold more diversified portfolios and are less prone to familiar behavioural traps such as the disposition effect and home bias. The mechanism is the reduction of information asymmetry: an advisor turns complex product features into insights that fit an individual's financial circumstances.

The Indian evidence points the same way. Prabha and Karthika (2022), studying retail investors in Tamil Nadu, found that consulting a financial advisor was the single strongest predictor of whether an investor chose growth-oriented equity funds over conservative debt instruments, even after income and education were accounted for. Chawla (2014) added an important observation from non-metropolitan India: there, MFDs act less as mere distribution channels and more as financial educators, especially for first-generation investors with no prior exposure to capital-market products.

Baker, Filbeck and Ricciardi (2017, 2019) examined the relationship from both sides, noting that advisors themselves carry biases that can dilute the quality of their advice. On balance, though, they conclude that the net effect on retail outcomes stays positive, mainly because advisors enforce discipline and discourage panic selling in downturns — a point that carries particular weight for semi-urban investors with limited market experience.

➢ *Digital Platforms and the Changing Information Ecosystem*

The spread of fintech platforms has been one of the more significant shifts in Indian financial markets since 2016. Apps such as Groww, Zerodha Coin, Kuvera, Paytm Money and ET Money have sharply lowered the cost and friction of

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investing. Singh and Kaur (2021) reported that digital-platform users in metropolitan India reviewed their investments more often and showed a closer fit between stated goals and actual fund choices than non-digital investors.

Outside the metros, the picture is more mixed. Rajaraman and Sundararajan (2020) found that digital-platform adoption in Tier-2 and Tier-3 cities went hand in hand with herd behaviour and recency bias, with investors clustering in recent top performers without much attention to risk. This tendency to chase past returns is well established in behavioural finance since Barber and Odean (2000), and it appears amplified on platforms whose home screens foreground whatever has performed best lately.

YouTube financial education adds another layer. Mishra and Tripathi (2023) surveyed 268 retail investors in Uttar Pradesh and found that 44.1% of those under 35 named YouTube channels as their main learning resource for mutual fund concepts — yet these same respondents scored lower on tests of balanced fund knowledge. The implication is that digital consumption tends to build awareness rather than genuine analytical capability.

➢ *Information Sources and Fund-Type Selection*

Bodla and Garg (2007) were among the first to study the information channels of Indian retail investors systematically, identifying brokers and agents as the dominant intermediaries in their Punjab sample. They found that intermediary-influenced investors leaned heavily toward diversified equity schemes, while those relying on newspapers and bank brochures concentrated in debt and liquid funds — an early empirical link between information source and scheme type.

Jain and Mandot (2012) revisited the question in Rajasthan and found that income and education moderated the link between information source and choice. High-income postgraduate respondents were far more likely to invest independently through direct plans and financial newspapers, whereas middle-income graduates depended most on MFD recommendations.

More recently, Sahi (2017) argued that behavioural biases do not operate evenly across channels. Investors receiving personalised advice showed lower rates of anchoring and availability bias than self-directed digital investors, which suggests that the face-to-face element of advisory work performs a real cognitive debiasing function.

➢ *Regional Studies and the Research Gap*

Gupta and Jain (2018) cautioned against the heavy reliance on pan-India or metropolitan samples in mutual fund research, arguing that cultural, linguistic and economic differences across states call for region-specific inquiry. Studies focused on Uttar Pradesh remain scarce. A notable exception is Yadav and Tiwari (2019), who studied 210 investors in Varanasi and Prayagraj and found that trust in the distributor's personal relationship outranked past returns, expense ratios and AMC brand in determining scheme selection.

Uttarakhand, though smaller as an investor market, offers an interesting setting because of its split economic geography: a relatively affluent urban corridor running through Dehradun, Haridwar and Roorkee alongside largely rural, tourism-dependent districts where financial infrastructure is thin. No published study has directly compared information-source dynamics across the urban and semi-urban strata of the state.

This paper addresses the gap by combining both states within a single survey framework. Doing so allows geographic and demographic disaggregation while retaining enough statistical power for inferential testing.

## III. RESEARCH METHODOLOGY

➢ *Research Design*

The study follows a descriptive-cum-analytical design. Quantitative primary data were collected through a structured questionnaire over four months, from October 2024 to January 2025. To accommodate the language preferences of respondents, the instrument was administered in both Hindi and English. No secondary data enter the analysis reported here.

➢ *Sampling Frame and Data Collection*

The target population was retail mutual fund investors living in Uttar Pradesh and Uttarakhand. To qualify, a respondent had to satisfy two conditions: current or past ownership of at least one mutual fund scheme, and at least one investment decision made in the previous twenty-four months. Fourteen locations were chosen to keep the sample geographically representative:

- Uttar Pradesh: Lucknow, Kanpur, Varanasi, Prayagraj, Agra, Noida/Greater Noida, Meerut, Gorakhpur and Bareilly.
- Uttarakhand: Dehradun, Haridwar, Roorkee, Haldwani and Rishikesh.

Stratified random sampling was applied, with stratification on three dimensions: geography (UP versus Uttarakhand), settlement type (urban, semi-urban, rural) and income category. This kept the sub-groups proportionally represented. Of the 410 questionnaires initially collected, 23 incomplete responses were removed, leaving a usable sample of 387 — a response effectiveness rate of 94.4%. A power analysis (Cohen, 1988) confirmed that 387 responses are enough to detect medium effect sizes ($f = 0.25$) at $\alpha = 0.05$ with power ($1 - \beta$) of at least 0.80 for both the ANOVA and the regression.

➢ *Measurement Instrument*

The questionnaire had four sections. Section A recorded demographic details (age, gender, education, occupation, monthly income and settlement type). Section B identified the primary information source the respondent relied on when selecting or evaluating mutual funds, offering five options:

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(1) Financial Advisor / MFD, (2) Digital Platforms (apps, websites, YouTube, social media), (3) Bank Relationship Manager, (4) Word of Mouth (family and friends), and (5) Traditional Media (newspapers, television).

Section C measured Investment Decision Quality (IDQ) through a six-item Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), adapted from Jain and Mandot (2012) and later validated for the Indian context by Singh and Kaur (2021). Sample items included 'My investment choices are aligned with my risk profile', 'I understand the fund I have invested in before investing', and 'I review my portfolio at regular intervals'. Cronbach's Alpha for the IDQ scale was 0.79, indicating satisfactory internal consistency.

Section D captured trust in the primary information source (a five-item scale, α = 0.81), preferred mutual fund category, investment frequency and investment horizon. Before full deployment the instrument was pilot-tested on 30 respondents in Lucknow and revised for clarity and language on the basis of their feedback.

➢ *Data Preparation and Analytical Framework*

This sub-section sets out the analytical process in full, in the order in which it was carried out — from data cleaning through variable construction to the specific tests applied to each hypothesis — so that the procedure can be assessed and, if required, replicated.

- *Data Screening and Cleaning*

All 410 returned questionnaires were entered into a coded SPSS worksheet, and every record was checked for three problems: incompleteness, out-of-range values, and internal contradictions (for example, a respondent who reported holding no mutual fund yet named a preferred fund category). Twenty-three records failed one or more of these checks and were dropped, leaving 387 usable responses. In the retained records, missing values were minimal — below 2% on any single variable — and were handled by listwise deletion for the particular test affected, so that no imputation was needed.

- *Variable Construction*

Categorical items — primary information source, preferred fund type, settlement type and occupation — were assigned numeric codes purely for tabulation and kept their nominal character in the analysis. The IDQ score was computed as the mean of the six Likert items in Section C, after the two negatively worded items were reverse-coded so that a higher composite value always signals better decision quality. The Financial Literacy score, used as a control in the regression, was built in the same spirit from a separate five-item objective-knowledge block covering diversification, expense ratio, the risk-return trade-off, SIP mechanics and taxation; it was scored as the number of correct answers and then rescaled onto a 0-5 range.

- *Reliability and Validity Checks*

Internal consistency was assessed with Cronbach's Alpha before any hypothesis was tested, returning 0.79 for the IDQ scale and 0.81 for the trust scale — both comfortably above the conventional 0.70 benchmark. Item-total correlations were inspected to make sure no single item was dragging down scale reliability; none was. Content validity rested on the pilot study and on the adaptation of established scales from Jain and Mandot (2012) and Singh and Kaur (2021).

The analysis then proceeded in four stages, each tied to a specific hypothesis.

- *Stage One — Descriptive Profiling*

Frequencies, percentages, means and standard deviations were generated to describe the sample and the distribution of the primary information source. These appear in Tables 1 and 2 and require no inferential assumptions.

- *Stage Two — Association Testing (H01 and H03)*

Pearson's Chi-square test of independence was used to check whether two categorical variables were related: information source against fund type for H01, and information source against each demographic variable for H03. For every contingency table the expected-cell-count rule was verified first (no more than 20% of cells below five); where a category was thin, such as Traditional Media, the low-frequency cells were examined to confirm the assumption still held. For each significant result, Cramér's V was computed alongside the Chi-square statistic so that the strength of association, and not merely its presence, could be judged.

- *Stage Three — Mean Comparison (H02)*

One-way ANOVA compared mean IDQ scores across the five information-source groups. Levene's test was run first and confirmed homogeneity of variance ($F = 1.87$, $p = 0.114$); because the assumption held, the standard F statistic was used rather than a Welch correction. A significant omnibus F was followed by Tukey's HSD post-hoc procedure to locate the specific group pairs that differed, since the omnibus test alone does not identify them. Eta-squared was reported as the effect-size measure.

- *Stage Four — Prediction (H04)*

Multiple linear regression modelled IDQ as a function of MFD usage, digital-platform usage, financial literacy, income and education. MFD usage and digital-platform usage were entered as dummy variables (1 = primary source, 0 = otherwise), with the remaining information-source categories forming the reference group. Before the coefficients were interpreted, the regression assumptions were tested in sequence: linearity and homoscedasticity through the residual-versus-fitted plot, normality of residuals through the normal P-P plot, independence of errors through the Durbin-Watson statistic (1.94, within the acceptable 1.5-2.5 band), and multicollinearity through the Variance Inflation Factors (maximum VIF = 2.14, well under the threshold of 5). Only once these checks were satisfied were the standardised beta coefficients reported and compared.

Across all stages a 5% significance level ($\alpha = 0.05$) served as the decision rule, with results significant at the 1% level flagged separately where relevant, and all tests were

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two-tailed. The analysis was carried out in IBM SPSS Statistics 26.0, and every table below was generated directly from the SPSS output rather than transcribed by hand, so as to remove transcription error.

## IV. RESULTS AND ANALYSIS

➢ *Demographic Profile of Respondents*

Table 1 Demographic Profile of the Sample (N = 387)

| Demographic Variable | Category | Frequency (%) |
|---|---|---|
| **Gender** | Male | 264 (68.2%) |
| | Female | 123 (31.8%) |
| **Age Group** | 18–25 Years | 47 (12.1%) |
| | 26–35 Years | 132 (34.1%) |
| | 36–45 Years | 112 (28.9%) |
| | 46–55 Years | 66 (17.1%) |
| | Above 55 Years | 30 (7.8%) |
| **Education** | Up to Class 12th | 33 (8.5%) |
| | Graduate | 164 (42.4%) |
| | Post-Graduate | 150 (38.8%) |
| | Professional Degree | 40 (10.3%) |
| **Occupation** | Salaried (Private Sector) | 136 (35.1%) |
| | Salaried (Govt./PSU) | 86 (22.2%) |
| | Self-Employed/Business | 109 (28.2%) |
| | Homemaker | 28 (7.2%) |
| | Student | 28 (7.3%) |
| **Monthly Income (INR)** | Below 25,000 | 55 (14.2%) |
| | 25,001–50,000 | 135 (34.9%) |
| | 50,001–1,00,000 | 128 (33.1%) |
| | Above 1,00,000 | 69 (17.8%) |
| **Settlement Type** | Urban | 225 (58.1%) |
| | Semi-Urban | 114 (29.5%) |
| | Rural | 48 (12.4%) |

Source: Primary Survey Data (N = 387).

The sample is demographically varied. Men make up 68.2% of respondents, broadly mirroring the documented gender gap in mutual fund ownership across North India. The core working-age cohort of 26 to 45 years accounts for 63% of the sample. Graduates and post-graduates together form 81.2%, consistent with the investor profile of Tier-2 cities in UP and Uttarakhand. Salaried employees, private and government combined, make up 57.3%, with a meaningful self-employed and business presence (28.2%). Income is concentrated in the INR 25,000-1,00,000 monthly band (68%), which matches AMFI's emerging-investor profile for B30 geographies.

➢ *Distribution of Primary Information Source*

Table 2 Primary Information Source for Mutual Fund Investment Decisions (N = 387)

| Primary Information Source | Frequency | Percentage (%) | Rank |
|---|---|---|---|
| Financial Advisor / MFD | 149 | 38.5% | 1st |
| Digital Platforms (Apps, Websites, YouTube, Social Media) | 136 | 35.1% | 2nd |
| Bank Relationship Manager | 42 | 10.9% | 3rd |
| Word of Mouth (Family / Friends) | 38 | 9.8% | 4th |
| Traditional Media (Newspapers, Television) | 22 | 5.7% | 5th |
| **Total** | **387** | **100.0%** | **—** |

Source: Primary Survey Data (N = 387).

Financial Advisors and MFDs remain the leading channel for 38.5% of investors surveyed, confirming that the human advisory network still counts in India's heartland states even as digital use rises. Digital platforms follow closely at 35.1%, a share that represents roughly a tripling of digital reliance compared with studies from this region conducted five to seven years ago. Bank Relationship Managers (10.9%), Word of Mouth (9.8%) and Traditional Media (5.7%) account for the remaining 26.4%, with Traditional Media falling especially sharply from the stronger position it held in pre-2018 surveys.

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➢ *Information Source Versus Fund-Type Preference (H01)*

Table 3 Cross-Tabulation — Primary Information Source vs. Preferred Fund Type

| Information Source | Equity (%) | Debt (%) | Hybrid (%) | Liquid/Other (%) |
|---|---|---|---|---|
| Financial Advisor / MFD | 41.6 | 28.2 | 22.8 | 7.4 |
| Digital Platforms | 58.8 | 11.8 | 22.1 | 7.3 |
| Bank Relationship Manager | 28.6 | 38.1 | 23.8 | 9.5 |
| Word of Mouth | 57.9 | 10.5 | 21.1 | 10.5 |
| Traditional Media | 31.8 | 27.3 | 27.3 | 13.6 |

Chi-square = 28.43 | df = 12 | p = 0.005 (significant at the 1% level). Cramér's V = 0.157 (weak-to-moderate association).

Fund-type preferences differ markedly across the information-source groups. Digital-platform users show the strongest concentration in equity funds (58.8%), in line with the tendency of platform algorithms to surface high-momentum past performers, which are disproportionately equity schemes. MFD-guided investors, by contrast, spread more evenly across equity (41.6%), debt (28.2%) and hybrid categories (22.8%), a pattern that points to advisor-mediated, goal-based allocation. Bank RM-influenced investors register the highest debt preference (38.1%), reflecting that channel's traditional orientation toward fixed-income products.

The Chi-square test returns $\chi^2 = 28.43$ (df = 12, $p = 0.005$), so H01 is rejected. The association between information source and fund-type preference is significant at the 1% level, indicating that the choice of channel is systematically linked to the category of fund invested in. The accompanying Cramér's V of 0.157 shows the association to be real but modest in strength.

➢ *Investment Decision Quality Across Information-Source Groups (H02)*

Table 4 Investment Decision Quality (IDQ) Scores by Information-Source Group

| Information Source Group | N | Mean IDQ | Std. Deviation | Rank |
|---|---|---|---|---|
| Financial Advisor / MFD | 149 | 3.91 | 0.72 | 1st |
| Digital Platforms | 136 | 3.54 | 0.88 | 2nd |
| Bank Relationship Manager | 42 | 3.48 | 0.81 | 3rd |
| Word of Mouth | 38 | 2.97 | 0.94 | 4th |
| Traditional Media | 22 | 2.84 | 1.02 | 5th |

One-way ANOVA: $F(4, 382) = 14.32$, $p < 0.001$. Levene's test: $F = 1.87$, $p = 0.114$ (homogeneity of variance satisfied). Eta-squared = 0.130 (moderate effect).

IDQ scores follow a clear and consistent order. MFD and Financial Advisor users report the highest mean (3.91, SD = 0.72), while Traditional Media consumers report the lowest (2.84, SD = 1.02); digital-platform users sit in second place (3.54, SD = 0.88). The between-group differences are significant ($F = 14.32$, $p < 0.001$), so H02 is rejected. Tukey HSD post-hoc tests confirm that the MFD group scores significantly higher than both the Word of Mouth group ($p < 0.001$) and the Traditional Media group ($p < 0.001$). The MFD-versus-digital difference is also significant ($p = 0.009$), though the practical gap there is narrower than in the other comparisons.

➢ *Demographic Determinants of Information-Source Choice (H03)*

Table 5 Chi-Square Tests — Demographic Variables vs. Primary Information Source

| Demographic Variable | Chi-Square Value | df | p-Value | Decision |
|---|---|---|---|---|
| Education Level | 32.16 | 12 | 0.001 | H03 Rejected |
| Monthly Income | 21.84 | 12 | 0.039 | H03 Rejected |
| Age Group | 24.78 | 16 | 0.074 | H03 Retained |
| Gender | 11.63 | 4 | 0.020 | H03 Rejected |
| Settlement Type (Urban/Semi-Urban/Rural) | 29.41 | 8 | 0.000 | H03 Rejected |

Source: Primary survey data. Decision rule: reject H03 where $p < 0.05$.

Education level shows the strongest association with information-source preference ($\chi^2 = 32.16$, $p = 0.001$). Post-graduate and professionally qualified respondents rely far more on digital platforms — 48.3% of post-graduates name digital platforms as their primary source — while graduates and below lean more heavily on MFDs (47.1% of graduates and 61.4% of those with up to Class 12 education). The pattern is consistent with financial education and digital literacy developing together, so that more educated investors are more comfortable navigating fintech platforms on their own.

Settlement type is the most powerful predictor among the demographic variables ($\chi^2 = 29.41$, $p < 0.001$). Urban respondents split almost evenly between MFDs (34.2%) and digital platforms (41.8%), semi-urban respondents lean

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toward MFDs (49.1%), and rural respondents are overwhelmingly MFD-dependent (73.0%) with minimal digital penetration (14.6%) — a finding that speaks directly to digital financial-inclusion policy in the two states.

Age on its own produces no significant association at the 5% level ($\chi^2 = 24.78$, $p = 0.074$), which suggests that the MFD-versus-digital divide is not primarily age-driven once education and settlement type are accounted for. Gender is significant ($p = 0.020$): female investors are proportionally more likely to rely on MFDs (44.7%) than male investors (35.6%).

- *Regression Analysis — Predictors of Investment Decision Quality (H04)*

Table 6 Multiple Linear Regression — Predictors of Investment Decision Quality (IDQ)

| Predictor Variable | B (Unstd.) | Std. Error | Beta (β) | t-Value | p |
|---|---|---|---|---|---|
| (Constant) | 0.821 | 0.214 | — | 3.84 | 0.000 |
| MFD / Financial Advisor Usage (Dummy) | 0.412 | 0.071 | 0.34 | 5.80 | 0.000 |
| Digital Platform Usage (Dummy) | 0.218 | 0.093 | 0.19 | 2.34 | 0.023 |
| Financial Literacy Score | 0.297 | 0.062 | 0.28 | 4.79 | 0.000 |
| Monthly Income Category | 0.126 | 0.063 | 0.14 | 2.00 | 0.048 |
| Education Level | 0.098 | 0.054 | 0.12 | 1.81 | 0.071 |

$R^2 = 0.413$ | Adjusted $R^2 = 0.404$ | $F(5, 381) = 53.67$ | $p < 0.001$ | Max VIF = 2.14 (multicollinearity acceptable) | Durbin-Watson = 1.94.

The model explains 41.3% of the variance in IDQ (Adjusted $R^2 = 0.404$), a robust figure for behavioural social-science research, and is significant overall ($F = 53.67$, $p < 0.001$). VIF values sit well below the accepted threshold of 5 (maximum 2.14), confirming that multicollinearity is not a problem.

MFD and Financial Advisor usage emerges as the single strongest predictor of decision quality ($\beta = 0.34$, $p < 0.001$), followed by the Financial Literacy score ($\beta = 0.28$, $p < 0.001$) and Digital Platform usage ($\beta = 0.19$, $p = 0.023$). Monthly income is significant but weaker ($\beta = 0.14$, $p = 0.048$). Education level does not reach significance once the other variables are held constant ($\beta = 0.12$, $p = 0.071$), which suggests that its effect on IDQ runs through financial literacy and information-source choice rather than operating directly.

H04 is therefore rejected. Both MFD engagement and digital-platform use significantly predict investment decision quality after financial literacy, income and education are controlled for. The gap between the two beta coefficients — 0.34 against 0.19 — captures the comparative advantage that personalised human advice holds over self-directed digital channels in producing higher-quality decisions among retail investors in UP and Uttarakhand.

## V. DISCUSSIONS

The results speak to three connected questions: how durable the human advisory channel really is in North India, what digital platforms do and do not deliver as information intermediaries, and what the pattern of information-source choice implies for investor welfare and regulation. Read against the existing literature, some findings confirm what earlier work would predict, while others sharpen or qualify it. This section takes each major finding in turn and sets it beside the studies that bear on it.

- *The Continued Dominance of the Human Advisory Channel*

That MFDs and financial advisors remain the leading source for 38.5% of respondents in 2024-25 sits comfortably with the older Indian evidence. Bodla and Garg (2007) had already identified brokers and agents as the dominant intermediaries in their Punjab sample, and Chawla (2014) argued that in non-metropolitan India the distributor functions as an educator rather than a simple transaction agent. Our data carry both claims into a two-state, post-fintech setting and show that the pattern has survived the arrival of Groww, Kuvera and the rest — something those earlier studies, written before the fintech surge, could not test.

Where the finding parts company with the prevailing metropolitan narrative is on the pace of disintermediation. The fintech-disruption literature, exemplified by Singh and Kaur (2021) on metropolitan India, implies a rapid displacement of human advisors; in UP and Uttarakhand that displacement is real but partial and uneven. The two accounts reconcile through geography — Singh and Kaur sampled metros, we sampled the heartland — which is precisely the kind of regional divergence Gupta and Jain (2018) warned would be lost in pan-India samples. In that sense our result is less a contradiction of the fintech literature than a boundary condition on it.

- *Advisory Channels and Decision Quality*

The higher IDQ of MFD-guided investors (3.91 against 3.54 for platform users) aligns with the international finding of Calcagno, Giofre and Urzua-Infante (2017) that advised households hold better-diversified, less bias-prone portfolios, and with Sahi's (2017) evidence that personalised advice lowers anchoring and availability bias relative to self-directed investing. Our contribution is to show that this advantage survives statistical control: the MFD beta of 0.34 holds after financial literacy and income are held constant, which weakens the competing explanation that advisors simply attract already-sophisticated clients.

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This matters because Baker, Filbeck and Ricciardi (2017) caution that the measured 'value' of an advisor is often confounded with client type — better clients self-select into advice. The regression here was designed to address exactly that selection concern, and the MFD coefficient remains both substantively meaningful and statistically robust once literacy and income are partialled out. The result thus offers a stronger, if still correlational, claim than most advisor studies in the Indian context, and it is consistent with the discipline-and-review mechanism that Chawla (2014) attributes to distributors in smaller markets.

- *Digital Platforms and Fund-Type Concentration*

The heavy tilt of platform users toward equity (58.8%) lines up almost exactly with Rajaraman and Sundararajan's (2020) account of recency bias and performance-chasing among Tier-2 digital investors, and with the classic Barber and Odean (2000) result that self-directed investors over-trade and chase past winners. It also complements Mishra and Tripathi's (2023) Uttar Pradesh finding that YouTube-educated young investors gain awareness without matching analytical depth. An investor who learns from an algorithmic feed or a video may well end up confident in equity without a corresponding grasp of suitability.

Our data add a dimension those studies did not measure. Rajaraman and Sundararajan inferred bias from behaviour, and Mishra and Tripathi from knowledge tests; we quantify the actual fund-type composition of platform users' choices and pair it with an independent decision-quality score. The convergence of a high equity share with a lower IDQ among the same group strengthens the case that platform-driven equity concentration is, at least in part, a suitability problem rather than a considered long-horizon strategy.

- *Demographic Moderation*

The education and settlement-type effects broadly replicate Jain and Mandot (2012), who found income and education moderating the information-source-to-choice relationship in Rajasthan. In our sample the better-educated lean digital and the less-educated lean on MFDs — the same moderation, running in the expected direction. The novel result is on settlement type: no earlier study we are aware of has shown rural investors in these states to be 73.0% MFD-dependent with only 14.6% digital reach. Yadav and Tiwari (2019) established the primacy of distributor trust in eastern UP; our finding helps explain why that trust is so decisive, since in rural areas the MFD is very often the only channel physically present.

- *Synthesis: Complementarity Rather Than Substitution*

Taken together, the findings support a complementarity reading of the advisor-platform relationship in these geographies rather than a straightforward substitution one. Digital platforms have widened access and now serve as the primary source for a third of investors, particularly the urban and educated; but they have not displaced the advisory function that produces higher-quality, better-diversified decisions, especially in semi-urban and rural strata. The two channels appear to serve different investor segments and different needs, and the policy question is less which one wins than how each can be strengthened where it is weakest.

The fund-type concentration among platform users also raises a governance point. Equity concentration is not inherently wrong for a long-horizon investor, but combined with the lower IDQ of the same group, the data suggest that a meaningful share of digital investors may be selecting equity without adequate risk comprehension. This echoes Rajaraman and Sundararajan (2020) and points to a real design challenge: how should SEBI's suitability framework adapt to digital distribution, where no human suitability assessment typically precedes fund selection?

Finally, the settlement-type result carries direct implications for SEBI's B30 incentive structure, which already grants enhanced trail commissions to MFDs for rural business. With 73.0% of rural investors depending on MFDs and only 14.6% reaching digital platforms, these incentives look structurally necessary and worth maintaining, because the MFD network remains effectively the only functional information channel in rural UP and Uttarakhand. In parallel, digital-inclusion investment by AMCs and fintechs in these areas should prioritise financial-literacy content — through YouTube, AMC apps and WhatsApp — alongside transaction facilitation, since information access has to precede meaningful digital adoption.

## VI. CONCLUSION

This study offers empirical evidence that the information source a retail investor relies on is a material determinant of mutual fund decision quality in Uttar Pradesh and Uttarakhand. Financial Advisors and MFDs remain the leading channel and are associated with the highest decision-quality scores, while digital platforms have quickly become the second-most common channel, especially among urban, educated and higher-income investors.

The significant association between information source and fund-type preference ($\chi^2 = 28.43$, $p = 0.005$), the significant between-group differences in decision quality ($F = 14.32$, $p < 0.001$), and the regression finding that MFD engagement is the strongest single predictor of IDQ ($\beta = 0.34$, $p < 0.001$) together establish that the information ecosystem an investor operates in shapes not just what they buy but how well-suited that choice is.

For AMCs working in UP and Uttarakhand, the practical message is twofold: keep investing in MFD capacity building, training and engagement, and at the same time develop digital advisory tools — goal-based calculators, risk-profiling engines and vernacular content — that can partly replicate the debiasing and goal-alignment functions of personalised advice for platform users. For SEBI and AMFI, the findings underline the continued need for MFD-centric B30 incentives, investor-awareness campaigns delivered through MFD networks in semi-urban and rural markets, and stronger digital suitability norms for direct and platform-based distribution.

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## LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

Several limitations should temper the interpretation of these findings. First, the cross-sectional design rules out causal inference; the associations and predictive relationships reported are robust, but the direction of the effect between information source and decision quality cannot be settled without longitudinal data. Second, although stratified, the sample is not a full probability sample of the investor population of the two states, so the results are best read as indicative rather than definitive. Third, self-reported IDQ scores carry some risk of social-desirability bias even with anonymity assured. Fourth, the study does not capture portfolio performance — the actual returns achieved — which would provide a more objective measure of decision quality. Fifth, digital-platform use is captured as a single dichotomous primary-source variable and so does not reflect varying intensities of engagement, such as frequency of app use, content consumption or subscription depth.

Future research could address these limitations through longitudinal designs that track investors over time, objective portfolio-performance data linked to information source, and graduated measures of digital engagement intensity. A qualitative follow-up with rural MFD-dependent investors would also help explain why distributor trust remains so decisive where digital access is thin.

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