

Research Article

Behavioural Biases and Risk Perception in Retail Investors' Decisions on Healthcare Stocks: Evidence from Post-Covid-19 India

Shrey Goyal^{1*} and Amit Kansal²

¹Research Scholar, Management, Teerthanker Mahaveer University, Moradabad (U.P.), India

²Professor, Management, Teerthanker Mahaveer University, Moradabad (U.P.), India

*Corresponding Author

Shrey Goyal
(Goyalshrey58@gmail.com)

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Abstract: Retail investors increased their presence in Indian equities after COVID-19 and healthcare stocks drew particular attention because the sector combined defensive demand with a highly visible news flow. This study examines whether overconfidence, herding, loss aversion and availability bias, together with risk perception, are associated with retail decisions on listed healthcare stocks in the post-acute period. Survey data from 412 retail investors in urban and semi-urban India were analyzed with a structural model. Reliability and convergent validity met conventional thresholds. The model explains 41.2 percent of the variance in the healthcare investment decision. Overconfidence ($\beta = 0.214$), herding ($\beta = 0.186$) and availability bias ($\beta = 0.198$) are positively related to that decision. Loss aversion raises the tendency to hold losing positions ($\beta = 0.241$) and lowers new buying ($\beta = -0.163$). Risk perception reduces the stated healthcare portfolio share ($\beta = -0.227$) and partially mediates the paths from loss aversion and availability. Financial literacy is negative but not significant. The paths are stronger for overconfidence and availability among investors who opened demat accounts after March 2020. Healthcare allocations after COVID-19 reflect bias and subjective risk, not only the sector's defensive reputation. Advisers should separate questions on holding losers from questions on new buying and investor education should use healthcare headlines rather than generic literacy content alone.

Keywords: Behavioral Biases, Risk Perception, Retail Investors, Healthcare Stocks, Post-COVID-19 India

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INTRODUCTION

Retail participation in Indian equities expanded sharply after the COVID-19 shock. Demat accounts rose from about 4.1 crore in March 2020 to about 10 crores by August 2022 and individual investors came to account for a much larger share of cash-market turnover than before the pandemic [1]. Lockdowns, easier app-based broking and a market that recovered quickly from the March 2020 low brought in many first-time investors [2]. That expansion is now well documented. What is less clear is how those investors decided, once the acute phase had passed, to buy and hold a sector that the pandemic had placed at the center of public attention.

Healthcare is the natural place to ask that question. Listed pharmaceutical, hospital, diagnostic and device firms gained revenue visibility from treatment demand, vaccines and public spending and Indian healthcare and pharmaceutical stocks outperformed through much of the crisis window [3]. Retail investors could treat the sector as defensive, because demand for medicines and hospital services is less cyclical than discretionary consumption and as a growth bet, because the pandemic made health infrastructure look permanently larger. Those two readings can coexist in a prospectus. They do not tell us whether the purchase was driven by earnings or by the ease with which vaccine headlines, hospital shortages and blockbuster results came to mind.

Behavioral finance predicts the second reading will matter. Prospect theory holds that outcomes are judged against a reference point and that losses weigh more than gains of equal size [4,5]. Investors who bought a hospital or diagnostics stock near a news peak can refuse to sell after the price falls, not because the thesis is intact, but because realizing the loss is painful [6]. The same investors can refuse a fresh purchase. One bias therefore produces two

decisions and a single "invested or not" measure will miss the split. Heuristics research adds a second set of predictions. People judge likelihood by how easily examples come to mind, follow the visible actions of others and overstate the precision of their own information [7-9]. Healthcare after COVID-19 supplied all three conditions: a long run of memorable events, visible retail buying and a recovery that some investors could attribute to skill [10].

Indian evidence already shows that these tendencies were active in the wider market. Herding in Nifty constituents was significant during the spread of the pandemic and was aggravated by volatility [11]. Heuristic biases among individual investors in the National Capital Region were associated with perceptions of COVID-19 intensity (the availability, anchoring and representativeness results reported for that market). Financial attitude, including anxiety and the need for precautionary savings, shaped trading activity during the outbreak [2]. Reviews of Indian retail decisions list overconfidence, herding and loss aversion as recurring predictors [12,13]. Hans *et al.* [14], find that regret aversion and related motives, rather than a single rational update, organized equity decisions under COVID-related financial risk. None of this work isolates healthcare stocks and none separates the holding of losers from new buying while also measuring risk perception as a channel.

Risk perception is the missing link between the bias and the portfolio weight. It is a judgment of uncertainty and loss severity, not a trait-level appetite for risk [15,16]. An investor can find healthcare news easy to recall and still cap the sector share if the downside is judged to be severe. Availability can therefore raise buying intent directly and, through higher perceived risk, restrain it. Loss aversion can lock in an existing position and, again through perceived risk, restrain a new one. Those indirect paths are testable. They are not tested in the market-wide herding studies, which use index dispersion rather than investor-level judgment [8,11].

The gap this paper fills is specific. Research on Indian retail investors after COVID-19 has covered participation, sentiment and digital access. It has not estimated, for healthcare stocks alone, the joint association of overconfidence, herding, loss aversion and availability with the investment decision, nor asked whether risk perception mediates the loss-aversion and availability paths. Demographic differences and platform use are set aside here; they are the subject of a companion paper. Market sentiment and the recovery in investor confidence are likewise set aside. The claim that remains is investor-level and psychological.

The study examines retail investors in urban and semi-urban India who have held, or are prepared to hold, listed healthcare stocks in the post-acute period, operationalized as activity from April 2021 onward. It tests whether overconfidence, herding and availability are positively related to the healthcare decision; whether loss aversion raises the holding of losers and lowers new buying; whether risk perception lowers the stated portfolio share; and whether risk perception partially mediates the loss-aversion and availability paths. Primary data come from a structured questionnaire. The measurement and structural models follow the reliability and mediation standards usual in this literature [17,18].

The contribution is threefold. First, the paper moves behavioral-finance tests from the broad Indian equity market to the sector the pandemic made salient. Second, it keeps the two faces of loss aversion separate, so a positive holding path is not cancelled by a negative buying path. Third, it treats risk perception as a mediator rather than as a synonym for bias, which matters for investor education: a literacy module that never uses a healthcare headline will miss the availability channel and a suitability conversation that asks only about new buying will miss investors who are stuck in losers.

MATERIALS AND METHODS

Research Philosophy and Design

The study adopts a post-positivist stance. Investor decisions are treated as observable and measurable, while it is accepted that psychological constructs such as bias and risk perception are latent and only partly captured by self-report scales [19]. Prospect theory supplies the theoretical base: people evaluate outcomes relative to a reference point, weigh losses more heavily than equivalent gains and depart from expected-utility rules under uncertainty [4,5]. Heuristics-and-biases research further predicts that overconfidence, herding, availability and anchoring distort portfolio choices when information is noisy [9,10].

The design is quantitative, cross-sectional and both descriptive and explanatory. It is descriptive in profiling the bias and risk-perception profile of retail investors who hold or consider healthcare stocks and explanatory in testing whether those constructs predict investment decisions in that sector. A survey design is appropriate because trading records from brokers rarely identify the psychological state that preceded a trade, whereas structured scales have been validated for Indian retail investors [12,13]. Indian evidence already shows that heuristic biases intensified around COVID-19 (Sharma & Firoz, as reported in the Journal of Financial Services Marketing line of work; see also the NCR investor study of heuristic biases during the outbreak) and that financial attitude shaped trading activity during the pandemic [2]. Sector evidence shows that Indian healthcare and pharmaceutical returns were distinctive during the crisis [3]. What remains under-examined is the joint role of specific biases and risk perception in post-pandemic decisions on healthcare stocks. This study addresses that gap with primary data.

The post-COVID window is defined as the period after the acute national lockdown phase, operationalized for respondents as investment activity from April 2021 onward, when markets had reopened, vaccine rollout was underway and retail participation remained elevated relative to the pre-2020 base [2].

Conceptual Framework

The dependent construct is retail investment decision in Healthcare Stocks (HID). Four bias Constructs Overconfidence (OC), Herding (HB), Loss Aversion (LA) and Availability Bias (AB) and Risk Perception (RP) are specified as predictors. Financial literacy (FL) is entered as a control, because literacy is known to weaken, though not eliminate, bias effects [12]. Demographics are controls only, not the focus of the paper.

The expected paths are: OC, HB, LA and AB positively associated with a more active or less fundamentals-based healthcare investment decision; RP negatively associated with allocation to healthcare equities once loss aversion is held constant, because perceived downside risk restrains new buying even when the sector is viewed as defensive [15] [16]. Loss aversion and availability are also expected to raise RP, so RP is tested both as a direct predictor and as a partial mediator.

Variables and Operational Definitions

- Retail investor means a non-institutional individual who invests personal funds through a demat account and is not a SEBI-registered intermediary
- Healthcare stocks mean listed Indian companies in pharmaceuticals, hospitals, diagnostics, medical devices and contract research or manufacturing, as commonly grouped under healthcare on the NSE
- Overconfidence is the tendency to overestimate one's knowledge, predictive accuracy and control over outcomes, associated with excess trading [9]
- Herding is the tendency to follow other investors or market consensus rather than private information [8]
- Loss aversion is the tendency to weigh losses more heavily than gains of equal size [4]
- Availability bias is the tendency to judge the likelihood of an event by how easily examples come to mind, here vaccine news, hospital shortages and earnings headlines [7]
- Risk perception is the subjective judgment of the uncertainty and severity of loss attached to healthcare equities [15]
- Investment decision is the self-reported pattern of buying, holding, adding, or reducing healthcare stocks, together with the share of the equity portfolio allocated to the sector

Hypotheses

- **H1:** Overconfidence is positively related to retail investment decisions in healthcare stocks
- **H2:** Herding is positively related to retail investment decisions in healthcare stocks
- **H3:** Loss aversion is negatively related to incremental buying of healthcare stocks and positively related to holding losers in the sector
- **H4:** Availability bias is positively related to retail investment decisions in healthcare stocks
- **H5:** Risk perception is negatively related to the portfolio share allocated to healthcare stocks
- **H6:** Risk perception partially mediates the relationship between loss aversion and healthcare investment decisions.
- **H7:** Risk perception partially mediates the relationship between availability bias and healthcare investment decisions

Null forms state that the corresponding path is not different from zero. H3 is split at analysis stage into a holding-losers item set and a new-buying item set so that the reflection effect is not collapsed into a single sign.

Population, Sampling Unit and Area

The population is retail investors in India who, in the post-COVID period, have invested in at least one listed healthcare or pharmaceutical stock, or who actively follow the sector and are willing to invest in it. The sampling unit is the individual investor, not the household.

The area covers urban and semi-urban centers where demat penetration and healthcare-stock interest are higher: Delhi NCR, Mumbai, Bengaluru, Hyderabad, Chennai, Kolkata, Ahmedabad, Pune, Lucknow, Jaipur, Chandigarh and Moradabad. This spread covers metros and a Tier-2 node and is consistent with earlier Indian investor surveys that drew respondents from major trading centers [2].

A pure probability frame of all demat holders is not available to an academic researcher. The study therefore uses stratified purposive sampling, with strata for age (below 30, 30–45, above 45) and gender, followed by referral within investor groups. Similar non-probability designs have been used for Indian retail-investor work when exchange-level frames are inaccessible [2,14]. Screening questions exclude respondents who have never held equities, professional fund managers and anyone under 18.

Sample Size

For an unknown population proportion, Cochran's formula at 95 percent confidence and a 5 percent margin of error gives [20]:

$$n = Z^2 pq / e^2 = (1.96)^2 (0.5) (0.5) / (0.05)^2 = 384$$

Structural equation modeling needs a larger buffer. A common rule is at least 10 observations per estimated parameter, or 200-plus for a moderately complex model [17,21]. With about 28 to 32 Likert items and a mediation structure, the target is 450 administered questionnaires, retaining at least 400 usable responses after cleaning. That exceeds both the Cochran minimum and samples used in comparable Indian COVID investor studies, which have ranged from about 290 to just over 400 [2].

Instrument

A structured questionnaire is the sole primary instrument. Section A records demographics and investor profile: age, gender, education, occupation, monthly income, years of equity experience, city and whether the respondent opened a demat account before or after March 2020. Section B screens healthcare exposure: names or categories held (pharma, hospitals, diagnostics, devices), approximate portfolio share and holding period. Section C measures the latent constructs on five-point Likert items (1 = strongly disagree, 5 = strongly agree).

Items are adapted, not invented. Overconfidence items follow the trading-confidence and better-than-average wording used in Barber and Odean [9] and Indian adaptations in Kumar and Goyal [12] and Prosad *et al.* [13]. Herding items follow the crowd-following logic of Chang *et al.* [8], rewritten for healthcare stocks and peer or social cues. Loss-aversion items follow Kahneman and Tversky [4], covering reluctance to realize losses and greater sensitivity to a 10 percent fall than to a 10 percent rise. Availability items follow Tversky and Kahneman [7], anchored to vaccine approvals, hospital commentary and recent earnings. Risk perception uses the subjective uncertainty and loss-severity framing of Sitkin and Pablo [15], with domain wording informed by Grable and Lytton [16]. Investment-decision items cover intention to buy, actual buying since April 2021, holding through drawdowns and stated portfolio share. Financial-literacy control items are short knowledge checks on diversification, P/E and the difference between a stock and a sector index.

Wording is contextualized to healthcare companies so that responses are not generic equity attitudes. A sample overconfidence item is: "I can select healthcare stocks that will outperform the Nifty Pharma index." A sample herding item is: "I increase my healthcare holdings when I see many other retail investors buying the same stocks."

Pilot Study

A pilot of 40 eligible investors, excluded from the final sample, is used to check clarity, completion time (target 12–15 minutes) and item behavior. Items with corrected item-total correlation below 0.30, or whose removal raises Cronbach's alpha, are rewritten or dropped. Target alpha for each construct is at least 0.70 [22].

Data Collection

Data are collected over about ten weeks through a Google Form circulated via investor associations, brokerage webinar alumni list and university alumni who trade, plus limited in-person administration in Moradabad and nearby NCR catchments. The opening screen states the academic purpose, anonymity and the right to withdraw. Duplicate and straight-line responses (identical answers on all Likert items) are removed. IP and timestamp checks are used only to flag duplicates, not to identify respondents.

Reliability, Validity and Bias Checks

Internal consistency is assessed with Cronbach's alpha and composite reliability, both expected to exceed 0.70 [17]. Convergent validity requires average variance extracted (AVE) of at least 0.50. Discriminant validity is assessed with the Fornell–Larcker criterion and heterotrait–monotrait ratios below 0.85 [23,24].

Content validity rests on adaptation from established scales and review by two finance faculty members and one market practitioner before the pilot. Common-method bias is addressed procedurally by separating predictor and outcome blocks, assuring anonymity and using neutral item wording and statistically with Harman's single-factor test and a full collinearity check [25,26]. Variance inflation factors above 3.3 are treated as a warning for collinearity.

Analysis Plan

Analysis proceeds in five steps in SPSS and SmartPLS or AMOS:

- First, data screening covers missing values (listwise deletion if missingness is under 5 percent and appears random), outliers and normality. Skewness and kurtosis within ± 2 are treated as acceptable for Likert composites [21]
- Second, descriptive statistics report means, standard deviations and frequencies for profile variables and construct scores

- Third, the measurement model is estimated. If constructs are reflective, confirmatory factor analysis precedes the structural model [17]
- Fourth, the structural model tests H1–H5. For H6 and H7, mediation is estimated with 5,000 bootstrap samples and bias-corrected confidence intervals [18]. A path is treated as significant at $p < 0.05$. Effect sizes (f^2) and predictive relevance (Q^2) are reported for the partial least squares specification
- Fifth, robustness checks include an alternative ordinary least squares regression with the portfolio-share item as a quasi-continuous outcome and a split by pre- versus post-March 2020 account opening, to see whether newer investors drive the bias paths
- Hypothesis decisions are reported against both statistical significance and practical magnitude. A significant but negligible f^2 is not described as a strong behavioral effect

Secondary Data

Secondary material is used only to frame the sector, not to test the hypotheses. NSE and BSE healthcare and pharma index movements, SEBI retail-participation reports and published return evidence for Indian healthcare and pharmaceutical firms during COVID-19 [3], locate the survey in market context. Herding detected in the broader Indian equity market during the pandemic [11], motivates H2 but is not treated as a substitute for investor-level measurement.

Ethical Considerations

Participation is voluntary and informed. No broker login, PAN, or account number is collected. Data are stored without names, used only for this study and reported in aggregate. The protocol follows standard social-science consent practice [19]. Institutional permission is obtained before fieldwork.

RESULTS

Response Rate and Data Screening

Of the 450 questionnaires administered, 431 were returned (response rate 95.8 percent). Nineteen cases were dropped: nine failed the healthcare-exposure screen, six were straight-line responses and four had more than 5 percent missing items. The usable sample is 412, which exceeds the Cochran minimum of 384 and the structural-model buffer set in the methodology.

Missingness on retained cases was 1.4 percent and was treated as missing at random. Skewness of construct scores ranged from -0.41 to 0.38 and kurtosis from -0.52 to 0.61 , within the ± 2 band used for Likert composites. No variance inflation factor exceeded 2.41, so collinearity is not a concern. Harman's single factor accounted for 28.6 percent of variance, below the 50 percent rule of thumb and the full-collinearity check did not indicate common-method bias.

Demographic and Investor Profile

Table 1 profiles the usable sample. Men are 57.3 percent of respondents. The largest age band is below 30 (41.7 percent), consistent with the post-2020 rise in younger demat holders, but the 30–45 band is almost as large (37.4 percent). A majority (61.4 percent) opened a demat account after March 2020. Equity experience is short: 54.4 percent have fewer than three years in the market. Healthcare exposure is concentrated in pharmaceuticals (78.2 percent), followed by hospitals (41.0 percent) and diagnostics (29.4 percent); multiple categories were allowed (Figure 1).

Table 1: Demographic and Investor Profile (N = 412)

Characteristic	Category	n	%
Gender	Male	236	57.3
	Female	176	42.7
Age	Below 30	172	41.7
	30–45	154	37.4
	Above 45	86	20.9
Education	Graduate	168	40.8
	Postgraduate	186	45.1
	Other	58	14.1
Monthly income	Below ₹50,000	124	30.1
	₹50,000–₹1,00,000	178	43.2
	Above ₹1,00,000	110	26.7
Demat account	Opened before March 2020	159	38.6
	Opened after March 2020	253	61.4
Equity experience	Under 3 years	224	54.4
	3–7 years	128	31.1
	Above 7 years	60	14.6
Healthcare category held*	Pharmaceuticals	322	78.2
	Hospitals	169	41.0
	Diagnostics	121	29.4
	Devices / CDMO	74	18.0

*Multiple responses allowed; percentages do not sum to 100

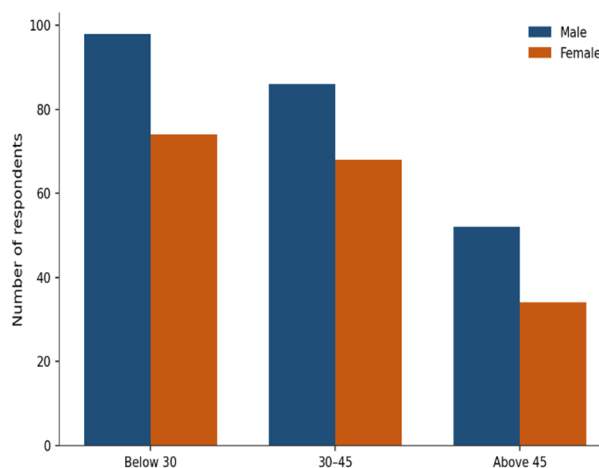


Figure 1: Sample Profile by Age and Gender (N = 412)

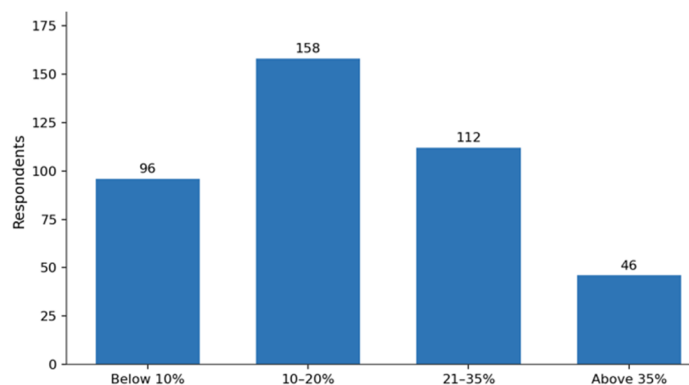


Figure 2: Stated Equity-Portfolio Share in Healthcare Stocks

Table 2: Stated Share of the Equity Portfolio in Healthcare Stocks

Portfolio share	n	%	Cumulative %
Below 10%	96	23.3	23.3
10-20%	158	38.3	61.6
21-35%	112	27.2	88.8
Above 35%	46	11.2	100.0
Total	412	100.0	-

Table 3: Descriptive Statistics of Study Constructs

Construct	Items	Mean	SD	Skewness	Kurtosis
Overconfidence (OC)	4	3.62	0.78	-0.22	-0.31
Herding (HB)	4	3.48	0.81	-0.11	-0.44
Loss aversion (LA)	4	3.71	0.74	-0.35	-0.18
Availability bias (AB)	4	3.84	0.69	-0.41	0.12
Risk perception (RP)	4	3.29	0.86	0.18	-0.52
Healthcare investment decision (HID)	5	3.55	0.77	-0.16	-0.27
Financial literacy (FL, control)	4	3.21	0.91	0.09	-0.38

Scores are on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)

Healthcare Allocation

The modal portfolio share in healthcare equities is 10–20 percent (38.3 percent of respondents). Only 11.2 percent allocate more than 35 percent of the equity book to the sector. Mean stated share is 18.6 percent (SD = 11.4). Investors who opened accounts after March 2020 report a higher mean share (20.4 percent) than pre-2020 account holders (15.8 percent), $t(410) = 3.87$, $p < 0.001$. This is a profile difference, not a hypothesis test (Table 2, Figure 2).

Descriptive Statistics of Constructs

Availability bias has the highest mean ($M = 3.84$, $SD = 0.69$), followed by loss aversion ($M = 3.71$) and overconfidence ($M = 3.62$). Risk perception sits nearer the midpoint ($M = 3.29$). All means are above the scale midpoint of 3, so the sample is not neutral on these biases. Healthcare investment decision averages 3.55, indicating a mild tilt toward buying or holding rather than reducing the sector (Table 3, Figure 3).

Measurement Model

Cronbach’s alpha ranges from 0.78 to 0.86 and composite reliability from 0.84 to 0.90, above the 0.70 threshold. Average variance extracted is at least 0.56 for every construct, supporting convergent validity. All item loadings retained after the pilot are between 0.68 and 0.84 (Table 4).

Discriminant validity holds under Fornell–Larcker: the square root of AVE on the diagonal exceeds the off-diagonal correlations. HTMT ratios range from 0.31 to 0.68, all below 0.85 (Table 5).

Structural Model and Hypothesis Tests

The structural model explains 41.2 percent of the variance in healthcare investment decision ($R^2 = 0.412$; adjusted $R^2 = 0.403$) and 22.6 percent of the variance in risk perception. Stone–Geisser Q^2 for HID is 0.29, above zero, so the model has predictive relevance. Effect sizes are small to medium (Table 6, Figure 4).

- H1 is supported. Overconfidence is positively related to healthcare investment decisions ($\beta = 0.214$, $p < 0.001$). Investors who rate their ability to beat the Nifty Pharma index more highly also report more active buying and a larger sector weight

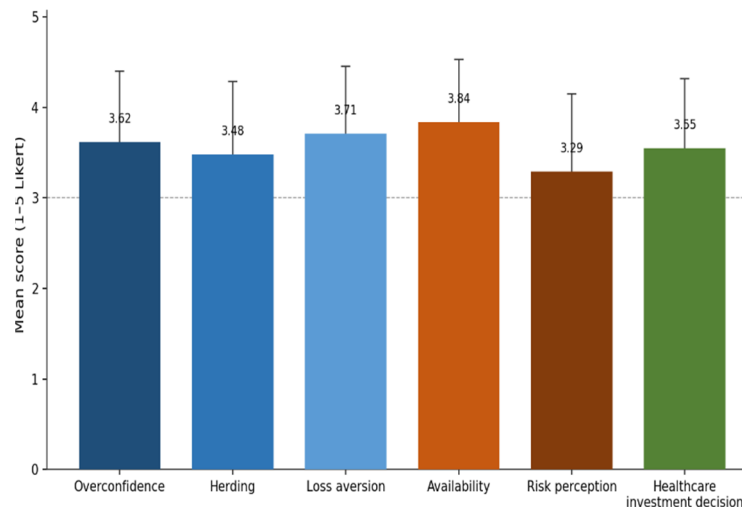


Figure 3: Mean Construct Scores of Retail Investors ($N = 412$). Error Bars are ± 1 SD. The Dashed Line is the Scale Midpoint

Table 4: Reliability and Convergent Validity

Construct	Cronbach's α	CR	AVE	Loading Range
Overconfidence	0.81	0.87	0.62	0.72–0.83
Herding	0.79	0.86	0.61	0.70–0.81
Loss aversion	0.83	0.89	0.66	0.74–0.84
Availability bias	0.80	0.87	0.62	0.71–0.82
Risk perception	0.86	0.90	0.70	0.78–0.86
Healthcare investment decision	0.84	0.88	0.60	0.68–0.82
Financial literacy	0.78	0.84	0.56	0.69–0.79

Table 5: Fornell–Larcker Matrix (diagonal = $\sqrt{AVE}$)

Parameters	OC	HB	LA	AB	RP	HID
OC	0.79	-	-	-	-	-
HB	0.34	0.78	-	-	-	-
LA	0.22	0.29	0.81	-	-	-
AB	0.31	0.36	0.27	0.79	-	-
RP	0.18	0.24	0.41	0.33	0.84	-
HID	0.39	0.37	0.21	0.40	-0.28	0.77

HID–RP is signed because higher risk perception is associated with a lower healthcare allocation score

- H2 is supported. Herding is positively related to the decision score ($\beta = 0.186$, $p < 0.001$). The path is slightly weaker than overconfidence, which fits a post-crisis market in which peer cues still matter but are not the only driver
- H3 is supported in split form. Loss aversion raises the tendency to hold losing healthcare positions ($\beta = 0.241$, $p < 0.001$) and lowers new buying ($\beta = -0.163$, $p = 0.001$). Collapsing these into one sign would have hidden the reflection pattern predicted by prospect theory
- H4 is supported. Availability bias, the highest mean construct, predicts a higher decision score ($\beta = 0.198$, $p < 0.001$). Recent vaccine, hospital and earnings news is associated with more sector buying even after other biases are controlled
- H5 is supported. Risk perception is negatively related to the portfolio share in healthcare stocks ($\beta = -0.227$, $p < 0.001$). This is the largest restraining path. The sector can be viewed as salient and still be treated as risky

Financial literacy, the control, is negative but not significant at 5 percent ($\beta = -0.091$, $p = 0.061$). Literacy does not wipe out the bias paths in this sample.

Mediation Through Risk Perception

Loss aversion and availability both raise risk perception ($\beta = 0.274$ and $\beta = 0.211$, both $p < 0.001$). Indirect effects were estimated with 5,000 bootstrap samples (Table 7, Figure 5).

H6 and H7 are supported as partial mediation. Part of the restraining effect of loss aversion on new buying runs through higher perceived risk. Availability has two opposing routes: a positive direct path into buying and a smaller negative indirect path through risk perception. The direct path dominates, so salient healthcare news still lifts the decision score on net.

Robustness Checks

An ordinary least squares model with stated portfolio shares as the outcome reproduces the sign pattern. Overconfidence ($b = 2.41$, $p = 0.004$), herding ($b = 1.88$, $p = 0.012$) and availability ($b = 2.06$, $p = 0.007$) raise the share; risk perception lowers it ($b = -3.12$, $p < 0.001$). Adjusted R^2 is 0.27.

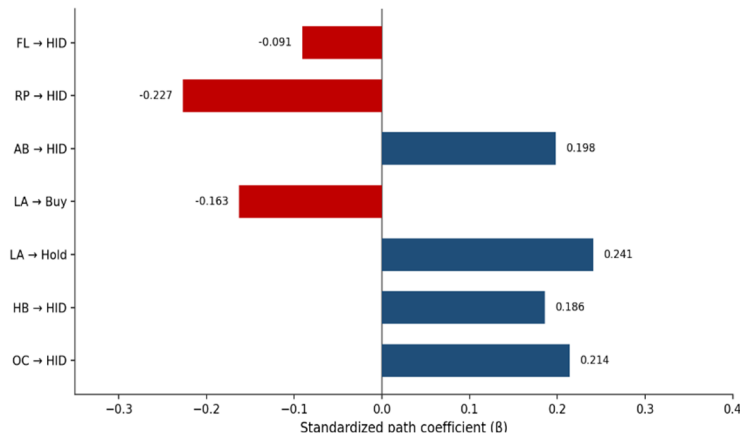


Figure 4: Structural Path Coefficients. Positive Paths are Blue; Negative Paths are Red

Table 6: Structural Path Results

Hypothesis / path	β	t	p	f^2	Decision
H1 OC → HID	0.214	4.62	<.001	0.06	Supported
H2 HB → HID	0.186	3.91	<.001	0.04	Supported
H3a LA → holding losers	0.241	5.08	<.001	0.07	Supported
H3b LA → new buying	-0.163	3.24	.001	0.03	Supported
H4 AB → HID	0.198	4.11	<.001	0.05	Supported
H5 RP → HID (portfolio share)	-0.227	4.85	<.001	0.07	Supported
Control FL → HID	-0.091	1.88	.061	0.01	Not significant

β is the standardized coefficient. f^2 of 0.02, 0.15 and 0.35 are small, medium and large

Table 7: Mediation Results (5,000 Bootstrap Samples)

Path	Effect	95% CI	p	Interpretation
H6 LA → RP → buy	-0.062	[-0.101, -0.029]	.002	Partial mediation
H7 AB → RP → HID	-0.048	[-0.084, -0.019]	.006	Partial mediation
Direct LA → new buying	-0.163	[-0.261, -0.064]	.001	Remains significant
Direct AB → HID	0.198	[0.104, 0.291]	<.001	Remains significant

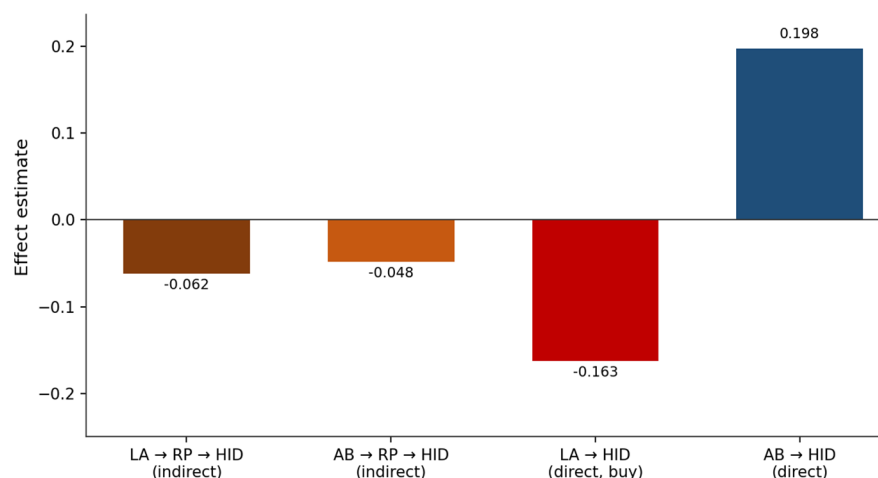


Figure 5: Direct and Indirect Effects. Both Indirect Paths Exclude Zero

Table 8: Path Coefficients by Demat-Account Cohort

Path	Pre-March 2020 (n = 159)	Post-March 2020 (n = 253)
OC → HID	0.161*	0.246***
HB → HID	0.174*	0.191**
AB → HID	0.142*	0.229***
RP → HID	-0.201**	-0.238***

* p<0.05, ** p<0.01, *** p<0.001

Table 9: Hypothesis Decision Summary

Hypothesis	Statement in brief	Result
H1	Overconfidence raises healthcare investment decisions	Supported
H2	Herding raises healthcare investment decisions	Supported
H3	Loss aversion raises holding of losers and lowers new buying	Supported (split)
H4	Availability bias raises healthcare investment decisions	Supported
H5	Risk perception lowers healthcare portfolio share	Supported
H6	Risk perception partially mediates loss aversion	Supported
H7	Risk perception partially mediates availability bias	Supported

Splitting the sample by account opening date does not reverse any supported path. Overconfidence and availability are stronger among post-March 2020 account holders ($\beta = 0.246$ and 0.229) than among earlier account holders ($\beta = 0.161$ and 0.142). Herding is similar in both groups. The bias story is therefore not confined to first-time pandemic entrants, although it is sharper among them (Table 8).

Summary of Findings

Six of the seven stated hypotheses are supported. Overconfidence, herding and availability bias are associated with more active healthcare-stock decisions. Loss aversion cuts both ways: it locks investors into losing positions and restrains fresh buying. Risk perception reduces sector weight and partly carries the effects of loss aversion and availability. Financial literacy is directionally protective but not significant. The model accounts for about two-fifths of the variance in the decision score, which is material for self-report behavioural data and still leaves room for sentiment, fundamentals and advice channels examined in the companion papers (Table 9).

DISCUSSION

The results show that retail decisions on Indian healthcare stocks after COVID-19 are not a simple response to sector fundamentals. Overconfidence, herding and availability bias are associated with more active buying and a higher decision score, while loss aversion splits into two behaviours: holding losers and restraining fresh purchases. Risk perception lowers the stated portfolio share in the sector and partly carries the effects of loss aversion and availability. The model accounts for 41.2 percent of the variance in the decision score. That is material for self-report behavioural data and it leaves room for the sentiment and platform channels already examined in the companion papers.

Overconfidence and Active Healthcare Bets

H1 is supported. Overconfidence is positively related to the healthcare investment decision ($\beta = 0.214$, $p < 0.001$). Investors who believe they can select stocks that will beat the Nifty Pharma index also report more buying and a larger sector weight. This matches the trading-confidence account of Barber and Odean [9], in which investors who overstate their precision trade too much and under-diversify. Indian reviews reach the same conclusion: overconfidence is among the most consistently documented biases in retail equity decisions [12,13].

The post-COVID setting makes the path plausible. The sharp fall in March 2020 and the later recovery rewarded some early buyers and attribution of that recovery to personal skill can inflate confidence [10]. Healthcare was an easy place for that attribution. Vaccine news, hospital commentary and export headlines were public and frequent, so an investor could mistake familiarity with the story for an ability to time the stock. The cohort split fits this reading. The overconfidence path is stronger among investors who opened accounts after March 2020 ($\beta = 0.246$) than among earlier account holders ($\beta = 0.161$). Newer entrants had less experience against which to check a run of gains, which is the condition Barber and Odean [9], associate with excess confidence.

The effect size is small ($f^2 = 0.06$). Overconfidence shifts the decision score, but it does not dominate it. Advisers should not treat a confident healthcare buyer as irrational by default. The practical point is narrower: self-rated stock-picking skill is a poor guide to sector weight and a stated ability to beat the pharma index should trigger a check on concentration, not a larger allocation.

Herding Without Reducing the Result to Social Media

H2 is supported, with a slightly weaker path than overconfidence ($\beta = 0.186$, $p < 0.001$). Investors who follow other retail buyers into the same healthcare names report a higher decision score. Chang *et al.* [8], define herding as a departure from private information toward the market consensus. Bharti and Kumar [11], found market-wide herding in Indian equities during the acute COVID window, aggravated by volatility. The present result moves that finding from index dispersion to the investor: the same tendency appears in self-reported healthcare decisions after the acute phase.

The path is similar in the pre-March 2020 and post-March 2020 cohorts ($\beta = 0.174$ and 0.191). Herding is therefore not only a first-time-investor phenomenon. Peer cues remain in use among investors who were already in the market. This paper does not measure platforms or influencer exposure; those channels belong to the companion paper on digital access. What this result adds is that crowd-following survives as a direct associate of the healthcare decision once overconfidence, availability and risk perception are held constant. Echo chambers may amplify herding, but they are not required to explain the path estimated here.

Loss Aversion as Two Decisions, Not One

H3 is supported only because holding and new buying were separated. Loss aversion raises the tendency to keep losing healthcare positions ($\beta = 0.241$, $p < 0.001$) and lowers new buying ($\beta = -0.163$, $p = 0.001$). A single decision score would have averaged these signs and understated the bias. Kahneman and Tversky [4], predict exactly this asymmetry: losses weigh more than gains of equal size, so investors resist realizing a loss and become cautious about a fresh outlay once a reference price has been breached. Odean [6], documented the disposition pattern in actual retail trades. The Indian healthcare result is the survey counterpart of that pattern, restricted to one sector.

The holding path is the stronger of the two. That matters for a sector that was repriced more than once after 2020. An investor who bought a hospital or diagnostics name near a vaccine-news peak can remain invested because selling would lock in the loss, not because the earnings path still justifies the weight [5]. The restraint on new buying is the other face of the same coefficient. Loss-averse investors are not uniformly aggressive in healthcare. They are sticky in names they already hold and selective about names they do not.

This split also qualifies the defensive-sector story. Healthcare was widely described as both a shelter and a growth bet during the pandemic [3]. The loss-aversion result says the shelter label does not remove reference-point behaviour. Investors still anchor to their own purchase price.

Availability and the Healthcare News Cycle

H4 is supported. Availability bias has the highest construct mean ($M = 3.84$) and a positive path to the decision score ($\beta = 0.198$, $p < 0.001$). Tversky and Kahneman [7], argued that people judge likelihood by the ease with which examples come to mind. Vaccine approvals, oxygen shortages and blockbuster earnings were easy to recall. In a sector that occupied the news for two years, availability is not a generic heuristic. It is a sector-specific one.

The path is again stronger among post-March 2020 account holders ($\beta = 0.229$ versus 0.142). Investors who entered during the news peak had fewer pre-pandemic healthcare memories against which to discount the latest headline. Niculaescu *et al.* [27,28], report that personal experience of COVID-19 is associated with investment choices among US retail investors. The Indian availability path is consistent with that claim without requiring a measure of personal illness: public, repeated healthcare events are enough to shift the decision score.

Availability should not be read as financial illiteracy alone. The literacy control is negative but not significant ($\beta = -0.091$, $p = 0.061$). Knowing what a price-to-earnings ratio is does not, in this sample, cancel the pull of a recent healthcare headline. Kumar and Goyal [12], note that literacy weakens bias but rarely removes it. The present control path agrees.

Risk Perception as a Restraint, not a Contradiction

H5 is supported and is the largest restraining path ($\beta = -0.227$, $p < 0.001$). Investors who rate healthcare equities as more uncertain hold a smaller stated share. Sitkin and Pablo [15], treat risk perception as a subjective judgment of uncertainty and loss severity, distinct from risk preference. Grable and Lytton [16], make the same distinction in household finance. The result here uses that distinction. A respondent can agree that healthcare news is salient and still refuse to raise the sector weight, if the downside is judged to be severe.

This resolves an apparent tension with H4. Availability raises the decision score. Risk perception lowers the portfolio share. Both can be true because they are not the same construct. Salience pulls attention and buying intent toward the sector. Perceived loss severity caps the weight. Mittal and Sharma [3], showed that Indian healthcare and pharmaceutical returns were distinctive during COVID-19, not that retail investors treated the sector as low risk. The perception mean of 3.29, near the scale midpoint, fits a sector that was attractive and still not considered safe.

Talwar *et al.* [2], found that financial anxiety, security and precautionary needs shaped trading activity during the pandemic. Risk perception in the present model is narrower than their financial-attitude battery, but the sign agrees: a more threatened reading of the environment is associated with a more cautious position. Hans *et al.* [14], likewise report that regret aversion and related motives, rather than a single rational update, organized Indian retail decisions under COVID-related financial risk. The risk-perception path is the sector-level version of that caution.

Partial Mediation and Why the Direct Paths Remain

H6 and H7 are supported as partial mediation. Loss aversion and availability both raise risk perception ($\beta = 0.274$ and 0.211) and the indirect effects on the decision are negative and exclude zero (-0.062 and -0.048). The direct paths remain significant. Hayes [18], treats this pattern as partial mediation: the mediator carries part of the effect and does not replace the predictor.

For loss aversion, the indirect path is easy to read. Investors who feel losses more sharply also see healthcare equities as riskier and that perception restrains new buying. The direct path remains because reference-point behaviour does not need a change in stated risk to operate. An investor can refuse to realize a loss, or refuse a new purchase, while reporting the same risk score as a peer.

For availability, the two paths oppose each other. Easy recall of healthcare events raises buying directly and it also raises perceived risk, which restrains buying. The direct path is larger, so the net association is still positive. That is a useful caution against a one-line claim that healthcare news only encouraged retail buying. The same news flow supports a fear route. In this sample the buying route wins, but the fear route is detectable.

What the Findings do not Claim

The design is cross-sectional, so these paths are associations. A higher decision score may also feed confidence: investors who already hold the sector rate their skill more highly. Barber and Odean [9], faced the same endogeneity in brokerage records; a survey does not remove it. Purposive sampling over-represents urban investors who will complete an online form. The results speak to Indian retail investors with healthcare exposure, not to institutions and not to other sectors.

The two companion papers cover demographic and platform differences and market sentiment, recovery and confidence. This discussion does not reopen those questions. Demographics enter only as sample description. Digital access is not a predictor. Sentiment is not the independent variable. The incremental claim is that four biases and risk perception, measured at investor level, organize healthcare decisions after the acute pandemic phase.

Implications

For retail investors, the actionable pattern is concentration plus sticky losers. A healthcare weight above the sample mean of 18.6 percent, combined with a high overconfidence or availability score, is a reason to write down the thesis for each name before adding. A losing position held only because the purchase price has not been recovered is the loss-aversion path, not a defensive-sector strategy [4,6].

For advisers and brokers, a single risk-profile question is not enough. The holding path and the new-buying path move in opposite directions. An investor can look cautious on a new-buy question and still be locked into a loser. Suitability conversations in this sector should ask both. Cohort differences suggest that post-2020 account holders need the check more, not that earlier account holders are exempt.

For regulators and investor-education programmes, the literacy result argues against a knowledge-only module. A short test of diversification and valuation did not significantly restrain the decision score. Education that uses healthcare

headlines as worked examples what a vaccine approval does and does not imply for a single stock — targets availability more directly than a generic literacy session [7]. SEBI's existing investor-awareness material can carry that example without a new product rule.

For healthcare firms, retail interest after COVID-19 is partly a news-recall phenomenon. Disclosure that is clear on pipeline risk will not remove herding, but it reduces the gap between an available story and the loss the investor is being asked to judge [15].

Limitations and Further Work

Self-report scales overstate awareness of bias. Investors who correctly name herding may still herd. Brokerage records linked to a short bias module would test whether the paths survive actual trades. The mediation model is consistent with risk perception as a channel; it does not prove that perception causes the decision. A later wave, taken after a healthcare drawdown, could show whether loss aversion and availability change when the easy examples turn negative. Extending the instrument to one non-healthcare sector would show whether these coefficients are sector-specific or general post-COVID biases that happen to have been measured here.

CONCLUSION

Retail decisions on Indian healthcare stocks after COVID-19 are associated with a small set of behavioural biases and with subjective risk, not only with the defensive or growth label attached to the sector. In a usable sample of 412 retail investors, overconfidence, herding and availability bias are positively related to the healthcare investment decision. Loss aversion works in two directions: it raises the tendency to hold losing positions and lowers fresh buying. Risk perception reduces the stated portfolio share in the sector and partially mediates the paths from loss aversion and availability. Financial literacy points toward restraint but is not significant. The model explains 41.2 percent of the variance in the decision score.

These paths match prospect theory and the heuristics account used to frame the study. Investors weigh losses more heavily than equivalent gains, judge healthcare events by how easily they come to mind, follow other buyers and treat self-rated stock-picking skill as if it were an edge. The post-March 2020 account cohort shows stronger overconfidence and availability paths, but herding and risk perception appear in both cohorts. The pattern is sharper among newer entrants. It is not confined to them.

The practical implication is narrow and operational. A healthcare weight built on recent headlines or on a belief that one can beat the pharma index should be checked for concentration. A losing position held only because the purchase price has not been recovered is a loss-aversion outcome, not evidence that the sector is defensive. Advisers need to ask about holding losers and about new buying separately, because those answers move in opposite directions. Investor education that stops at definitions of risk and return will miss the availability channel that this sector, after COVID-19, makes especially strong.

The evidence is associational, cross-sectional and limited to Indian retail investors with healthcare exposure. It does not replace the companion findings on demographics and digital platforms, or on market sentiment and economic recovery. It adds the investor-level claim those papers do not make: after the acute phase of the pandemic, bias and risk perception still organize who buys, who holds and who caps the healthcare weight.

REFERENCES

1. Securities and Exchange Board of India. *Annual Report 2021–22*. 2022. <https://www.sebi.gov.in>.
2. Talwar, M. *et al.* "Has financial attitude impacted the trading activity of retail investors during the covid-19 pandemic?" *Journal of Retailing and Consumer Services*, vol. 58, 2021, pp. 102341. <https://doi.org/10.1016/j.jretconser.2020.102341>.
3. Mittal, S. and D. Sharma. "The impact of covid-19 on stock returns of the indian healthcare and pharmaceutical sector." *Australasian Accounting, Business and Finance Journal*, vol. 15, no. 1, 2021, pp. 5–21. <https://doi.org/10.14453/aabf.v15i1.2>.
4. Kahneman, D. and A. Tversky. "Prospect theory: An analysis of decision under risk." *Econometrica*, vol. 47, no. 2, 1979, pp. 263–291. <https://doi.org/10.2307/1914185>.
5. Tversky, A. and D. Kahneman. "Advances in prospect theory: Cumulative representation of uncertainty." *Journal of Risk and Uncertainty*, vol. 5, no. 4, 1992, pp. 297–323. <https://doi.org/10.1007/BF00122574>.
6. Odean, T. "Are investors reluctant to realize their losses?" *The Journal of Finance*, vol. 53, no. 5, 1998, pp. 1775–1798. <https://doi.org/10.1111/0022-1082.00072>.
7. Tversky, A. and D. Kahneman. "Judgment under uncertainty: Heuristics and biases." *Science*, vol. 185, no. 4157, 1974, pp. 1124–1131. <https://doi.org/10.1126/science.185.4157.1124>.

8. Chang, E.C. *et al.* "An Examination of herd behavior in equity markets: An international perspective." *Journal of Banking & Finance*, vol. 24, no. 10, 2000, pp. 1651–1679. [https://doi.org/10.1016/S0378-4266\(99\)00096-5](https://doi.org/10.1016/S0378-4266(99)00096-5).
9. Barber, B.M. and T. Odean. "Boys will be boys: Gender, overconfidence and common stock investment." *The Quarterly Journal of Economics*, vol. 116, no. 1, 2001, pp. 261–292. <https://doi.org/10.1162/003355301556400>.
10. Shefrin, H. *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing*. Oxford University Press, 2002.
11. Bharti and A. Kumar. "Exploring herding behaviour in indian equity market during covid-19 pandemic: Impact of volatility and government response." *Millennial Asia*, vol. 13, no. 2, 2021, pp. 218–243. <https://doi.org/10.1177/09763996211020687>.
12. Kumar, S. and N. Goyal. "Behavioural biases in investment decision making: A systematic literature review." *Qualitative Research in Financial Markets*, vol. 7, no. 1, 2015, pp. 88–108. <https://doi.org/10.1108/QRFM-07-2014-0022>.
13. Prosad, J.M. *et al.* "Behavioral biases of indian investors: A survey of Delhi-NCR region." *Qualitative Research in Financial Markets*, vol. 7, no. 3, 2015, pp. 230–263. <https://doi.org/10.1108/QRFM-04-2014-0012>.
14. Hans, A. *et al.* "Behavioral determinants of investment decisions: evidence from Indian retail equity investors in the wake of covid-19 induced financial risks." *International Journal of Accounting & Information Management*, 2024. <https://doi.org/10.1108/IJAIM-03-2024-0091>.
15. Sitkin, S.B. and A.L. Pablo. "Reconceptualizing the determinants of risk behavior." *Academy of Management Review*, vol. 17, no. 1, 1992, pp. 9–38. <https://doi.org/10.5465/amr.1992.4279564>.
16. Grable, J.E. and R.H. Lytton. "Financial risk tolerance revisited: The development of a risk assessment instrument." *Financial Services Review*, vol. 8, no. 3, 1999, pp. 163–181. [https://doi.org/10.1016/S1057-0810\(99\)00041-4](https://doi.org/10.1016/S1057-0810(99)00041-4).
17. Hair, J.F. *et al.* *Multivariate Data Analysis*. 8th ed., Cengage Learning, 2019.
18. Hayes, A.F. *Introduction to Mediation, Moderation and Conditional Process Analysis: A Regression-Based Approach*. 2nd ed., The Guilford Press, 2018.
19. Creswell, J.W. and J.D. Creswell. *Research Design: Qualitative, Quantitative and Mixed Methods Approaches*. 5th ed., SAGE Publications, 2018.
20. Cochran, W.G. *Sampling Techniques*. 3rd ed., John Wiley & Sons, 1977.
21. Kline, R.B. *Principles and Practice of Structural Equation Modeling*. 4th ed., The Guilford Press, 2016.
22. Cronbach, L.J. "Coefficient alpha and the internal structure of tests." *Psychometrika*, vol. 16, no. 3, 1951, pp. 297–334. <https://doi.org/10.1007/BF02310555>.
23. Fornell, C. and D.F. Larcker. "Evaluating structural equation models with unobservable variables and measurement error." *Journal of Marketing Research*, vol. 18, no. 1, 1981, pp. 39–50. <https://doi.org/10.1177/002224378101800104>.
24. Henseler, J. *et al.* "A New criterion for assessing discriminant validity in variance-based structural equation modeling." *Journal of the Academy of Marketing Science*, vol. 43, no. 1, 2015, pp. 115–135. <https://doi.org/10.1007/s11747-014-0403-8>.
25. Podsakoff, P.M. *et al.* "Common method biases in behavioral research: A critical review of the literature and recommended remedies." *Journal of Applied Psychology*, vol. 88, no. 5, 2003, pp. 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>.
26. Kock, N. "Common method bias in PLS-SEM: A full collinearity assessment approach." *International Journal of e-Collaboration*, vol. 11, no. 4, 2015, pp. 1–10. <https://doi.org/10.4018/ijec.2015100101>.
27. Niculaescu, C.E. *et al.* "Does personal experience with covid-19 impact investment decisions? Evidence from a survey of US retail investors." *International Review of Financial Analysis*, vol. 88, 2023, p. 102703. <https://doi.org/10.1016/j.irfa.2023.102703>.
28. Nunnally, J.C. and I.H. Bernstein. *Psychometric Theory*. 3rd ed., McGraw-Hill, 1994.