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Gold Volatility and Trader Psychology: A Longitudinal Behavioral Finance Study

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Abstract: This study explores the relationship between gold price volatility and trader psychology over a five-year period (2020–2024) using a longitudinal mixed-method approach grounded in behavioral finance. Gold is traditionally regarded as a safe-haven asset, an inflation hedge, and a store of value. However, the selected period experienced significant volatility driven by global disruptions such as the COVID-19 pandemic, inflationary pressures, economic uncertainty, and geopolitical instability. While conventional financial theories attribute gold price movements to macroeconomic variables—such as inflation, interest rates, exchange rates, and geopolitical risks—these models assume rational investor behavior. This research challenges that assumption by incorporating behavioral factors including risk aversion, herd behavior, anchoring bias, investor sentiment, and trading activity. The study combines secondary gold price data with primary survey responses collected from 100 experienced traders through a structured yes/no questionnaire. A volatility dispersion ratio is calculated using six-month high–low price ranges for each year. Statistical techniques including descriptive analysis, Pearson correlation, regression, and mediation modeling are applied to test five hypotheses. Findings indicate that increased volatility is associated with higher risk aversion, stronger herd tendencies, and greater reliance on past price benchmarks. Investor sentiment emerges as the most influential factor and partially mediates the relationship between volatility and trading behavior. The study proposes a behavioral amplification mechanism, where market uncertainty intensifies emotional responses, influencing trading decisions and further contributing to price instability. This research contributes to behavioral finance, commodity market analysis, and investor psychology by presenting an integrated framework linking price volatility with trader behavior. It also offers practical insights for improving risk awareness and behavioral strategies in trading environments.

Keywords: Gold price volatility; Behavioral finance; Trader psychology; Risk aversion; Herd behavior; Anchoring bias; Investor sentiment; Prospect theory; Commodity markets; Mediation analysis; Longitudinal study

I. STUDY OVERVIEW

Disclaimer: This study is intended solely for academic and research purposes. The findings are based on collected data and should not be interpreted as financial or investment advice. Participation in the survey was voluntary, and respondent confidentiality has been maintained. The author does not hold professional certification in financial advisory services. Any decisions made based on this study are the responsibility of the reader.

Study Overview: This research analyses how fluctuations in gold prices influence trader psychology during 2020–2024, a period marked by economic and geopolitical disruptions. A longitudinal mixed-method design is adopted, combining historical price data with survey responses from experienced traders. The study focuses on key behavioral dimensions such as risk aversion, herd behavior, anchoring bias, sentiment sensitivity, and trading frequency. Analytical tools including descriptive statistics, correlation analysis, regression modeling, and mediation analysis are used to examine the relationship between volatility and behavioral patterns. The findings suggest that rising volatility intensifies emotional and cognitive biases among traders, significantly influencing their decision-making. The study proposes a behavioral-volatility framework explaining the interaction between market fluctuations and psychological responses.

II. INTRODUCTION

A. Background of the Study

The period from 2020 to 2024 represents a phase of heightened market turbulence, characterized by irregular and clustered price movements. This environment provides a strong basis for examining the Adaptive Market Hypothesis, which suggests that investor behavior evolves in response to changing market conditions. Gold has historically served multiple roles—as an inflation hedge, a safe-haven asset, and a stabilizing investment. During this period, gold prices experienced sharp increases and corrections due to global uncertainty.

Major events such as the COVID-19 pandemic, supply chain disruptions, expansionary fiscal policies, inflation, and geopolitical conflicts—including the Russia–Ukraine war—contributed to repeated volatility. Gold prices notably crossed USD 2000 during these periods. Such fluctuations create an opportunity to analyze how traders respond psychologically to uncertainty. Unlike equity markets, gold markets are particularly sensitive to fear and macroeconomic instability, making them ideal for behavioral analysis.

B. *Statement of the Problem*

Despite extensive research on macroeconomic determinants of gold prices, limited studies integrate behavioral factors with long-term volatility analysis. Key gaps include:

- The impact of volatility on trader decision-making
- The role of psychological biases in extreme price movements
- The evolution of investor sentiment over time

Despite the recognition of psychological factors in financial decision-making, limited empirical studies have systematically examined their interaction with commodity price volatility over time, particularly in emerging market contexts.

C. *Research Objectives*

- To examine six-month high and low gold prices for each year (2020–2024)
- To evaluate trader psychological behavior during volatile periods
- To analyze the relationship between volatility and behavioral biases
- To develop a behavioral-volatility framework

These objectives collectively aim to bridge the gap between traditional financial models and behavioral insights, contributing to a more holistic understanding of market dynamics. The objective of this study is not to measure how strongly a trader feels, but whether the behavioral bias exists under conditions of volatility.

D. *Research Questions*

- Does increased volatility lead to greater risk aversion?
- Are extreme prices associated with herd behavior?
- Do traders anchor decisions to past price levels?
- Does investor sentiment mediate trading behavior?

E. *Research Hypotheses*

- H1: Gold price volatility is positively related to risk aversion
- H2: Extreme price levels influence herd behavior
- H3: Traders exhibit anchoring bias toward past prices
- H4: Behavioral biases affect trading frequency
- H5: Investor sentiment mediates the volatility–behavior relationship

F. *Significance of the Study*

This study contributes to:

- Behavioral finance theory by integrating psychology with volatility
- Commodity market research
- Risk management and trading strategies
- Understanding investor decision-making

The study also holds practical relevance for traders by highlighting the importance of behavioral awareness in managing risk during volatile market conditions.

G. *Scope of the Study*

The study focuses on gold market behavior between 2020 and 2024. It combines price data with survey responses from experienced traders. Key behavioral variables include risk aversion, herd behavior, anchoring bias, sentiment, and trading frequency. Statistical techniques such as correlation, regression, and mediation analysis are applied. The study is analytical and behavioral in nature, aiming to explain how volatility influences trader psychology.

III. REVIEW OF LITERATURE

A. Introduction

This chapter provides a theoretical foundation for understanding the relationship between gold price volatility and trader psychology. While traditional finance emphasizes macroeconomic factors, behavioral finance highlights the role of human psychology.

B. Traditional Theories of Gold Pricing:

Gold prices are commonly influenced by:

- Inflation
- Interest rates
- Currency movements
- Geopolitical risks

Gold is widely regarded as a hedge, a safe-haven, and a store of value. However, these models assume rational behavior.

C. Behavioral Finance Theory

Behavioral finance challenges rationality by incorporating psychological biases. Key contributors include Kahneman, Tversky, Thaler, and Shiller.

Common Biases

- Loss Aversion: Losses impact more than gains
- Overconfidence: Overestimation of ability
- Herd Behavior: Following others' actions
- Anchoring Bias: Reliance on past price levels

The foundational work of scholars associated with Prospect Theory emphasizes that investor decisions are often influenced by perceived gains and losses rather than absolute outcomes, making it particularly relevant in volatile commodity markets.

D. Prospect Theory

Prospect theory explains decision-making under risk:

- Losses are felt more strongly than gains
- Risk-taking increases after losses
- Risk aversion increases after gains

E. Investor Sentiment

Investor sentiment reflects collective emotions and significantly affects market trends. In gold markets, fear and uncertainty often increase demand. Investor sentiment not only reflects market mood but also acts as a transmission mechanism through which external shocks influence trading behavior.

F. Behavioral Dynamics in Commodity Markets

Commodity markets are highly sensitive to global events. Behavioral patterns include:

- Herding during crises
- Anchoring to historical prices
- Emotion-driven trading

G. Research Gap

Key gaps include:

- Lack of integration between volatility and behavioral data
- Limited direct measurement of trader psychology
- Insufficient focus on sentiment as a mediator

This gap highlights the need for an integrated framework that captures both market-driven volatility and investor-driven behavioral responses over time.

H. Conceptual Framework

Gold Price Volatility → Investor Sentiment → Behavioral Bias → Trading Activity

The proposed framework assumes a directional relationship where volatility influences sentiment, which in turn shapes behavioral biases and trading actions.

I. Chapter Summary

This chapter highlights that while traditional models explain price movements through macroeconomic factors, behavioral finance emphasizes psychological influences. The study bridges this gap by combining quantitative and behavioral approaches.

IV. RESEARCH METHODOLOGY

A. Introduction

This chapter explains the research design, data sources, sampling framework, analytical tools, and methodological choices used in the study. It also justifies why specific methods were selected and why alternative approaches were not adopted. The study follows a structured approach to examine the relationship between gold price volatility and trader psychology within the context of Kolhapur city.

B. Research Design

The study adopts a longitudinal mixed-method research design.

Longitudinal Approach: The study analyses gold price data over a five-year period (2020–2024), allowing observation of trends and behavioral changes over time. Mixed-Method Approach: Combines: Quantitative data (gold price fluctuations), Qualitative/behavioral data (trader survey responses)

Why this design was used: Captures both numerical volatility and human behavior, Provides a comprehensive understanding of market dynamics, Helps establish cause-effect relationships over time

Why other designs were not used: Cross-sectional design was not used because it captures data at a single point in time and cannot explain behavioral changes across different market phases. Purely qualitative methods were avoided as they lack statistical validation. Experimental design was not feasible due to real-world market constraints and inability to control variables like global price movements.

This design ensures that both objective market movements and subjective behavioral responses are analyzed in a complementary manner, enhancing the robustness of the study.

C. Study Area

Kolhapur City: The study is conducted in Kolhapur city, Maharashtra, a well-known commercial hub with active participation in gold trading and investment activities.

Reasons for selecting Kolhapur: Strong cultural and economic association with gold as an investment and ornament, Presence of: Gold traders, Jewellery businesses and Commodity investors. Accessibility to experienced respondents for primary data collection. Represents a semi-urban financial behavior model, bridging rural and metropolitan investor psychology. Why other areas were not selected: Metropolitan cities (like Mumbai) may reflect highly institutionalized trading behavior, which may not represent typical individual traders. Rural areas may lack sufficient exposure to structured trading practices. Kolhapur offers a balanced and practical research environment.

D. Data Collection

The study uses both primary and secondary data.

3.4.1 Primary Data: Collected through a structured questionnaire (Yes/No format), Respondents: 100 experienced traders in Kolhapur.

Focus areas: Risk aversion, Herd behavior, Anchoring bias, Investor sentiment, trading frequency

Why structured questionnaire was used: Ensures uniformity in responses, Simplifies statistical analysis, and Reduces ambiguity in interpretation. Why other methods were not used: Unstructured interviews were avoided due to difficulty in quantification, Open-ended surveys may introduce subjective bias and complexity in coding, and Focus groups were not used due to time constraints and group influence bias

The study adopts a binary (Yes/No) response format to capture clear and decisive behavioral tendencies among traders. This approach minimizes ambiguity, reduces respondent fatigue, and ensures higher response reliability, particularly when dealing with experienced participants who are expected to have well-formed opinions. Unlike Likert scales, which measure degrees of agreement, the binary format is more suitable for identifying the presence or absence of specific behavioral biases such as risk aversion, herd behavior, and anchoring. This aligns with the objective of the study, which is to detect behavioral tendencies rather than measure their intensity.

3.4.2 Secondary Data: Gold price data (2020–2024) Six-month high and low prices for each year.

Sources: Financial market reports, Commodity market records.

Why secondary data was used: Provides objective and historical market information, Necessary for calculating volatility.

E. Sampling Design

Sampling Method: Purposive Sampling, Only experienced traders were selected, Ensures respondents have relevant market knowledge. Sample Size: 100 respondents

Why purposive sampling was used: Targets individuals with practical trading experience, Improves data relevance and quality. Why other sampling methods were not used: Random sampling may include inexperienced participants, Stratified sampling was not required due to the focused group, and Convenience sampling may reduce reliability.

The selection of experienced traders improves the reliability of responses, as participants possess practical exposure to market volatility and decision-making.

F. Variables of the Study

- Independent Variable: Gold price volatility
- Dependent Variables: Risk aversion, Herd behavior, Anchoring bias, Trading frequency
- Mediating Variable: Investor sentiment

G. Measurement of Variables

Gold Price Volatility

Measured using a Volatility Dispersion Ratio:

Volatility = (6-month High − 6-month Low) / Average Price

Behavioral Variables: Measured using binary responses (Yes = 1, No = 0)

The use of a structured and consistent measurement approach allows for comparability across respondents and ensures clarity in statistical interpretation.

H. Tools and Techniques of Analysis

The study uses the following statistical tools:

1. Descriptive Statistics: Mean, percentage, standard deviation: Used to summarize data
2. Pearson Correlation: Measures relationship between volatility and behavioral variables
3. Regression Analysis: Examines impact of volatility on trader behavior
4. Mediation Analysis: Tests whether investor sentiment acts as an intermediate variable

Why these tools were used: Suitable for quantitative behavioral analysis, Provide clear statistical relationships, widely accepted in behavioral finance research. Why other tools were not used: Advanced machine learning models were not used due to limited sample size, Time-series econometric models (like ARIMA/GARCH) were not applied as the study focuses more on behavioral relationships than forecasting, Factor analysis was not required due to predefined variables

Since the data is binary, mean values are interpreted as probabilities of agreement, representing the proportion of respondents exhibiting a particular behavioral trait.

These techniques are widely used in behavioral finance research to establish relationships between psychological constructs and market variables.

I. Hypothesis Testing

All hypotheses are tested using: Correlation analysis, Regression models, Mediation framework.

Significance is evaluated at standard statistical levels (e.g., 5%).

J. Reliability and Validity

Reliability: Ensured through structured questionnaire, Consistent measurement across respondents

Validity, Content validity ensured through literature review, Questions aligned with behavioral finance constructs. Although Cronbach's Alpha is commonly used for Likert-scale data, the present study ensures reliability through a structured questionnaire, consistent binary coding, and focused construct design. Each construct is measured using multiple statements to maintain internal consistency.

K. Limitations of the Methodology

Limited sample size (100 traders), Geographic restriction to Kolhapur city, Binary responses may oversimplify complex behavior, Dependence on self-reported data. Despite these limitations, the study provides meaningful insights into trader behavior within the defined research context. The use of a binary response format may limit the ability to capture the intensity of psychological constructs. However, this limitation is mitigated by the study's focus on behavioral presence rather than gradation. Future research may adopt Likert-scale instruments to examine the strength of these behaviours in greater detail.

L. Ethical Considerations

Participation was voluntary, Confidentiality of respondents maintained

Data used only for academic purposes,

M. Chapter Summary

This chapter outlined the methodological framework used in the study. A longitudinal mixed-method design was adopted to integrate market data with behavioral insights. The study focused on Kolhapur city and used purposive sampling to collect relevant primary data. Statistical tools such as correlation, regression, and mediation analysis were applied to examine the relationship between gold price volatility and trader psychology. Binary measurement is commonly used in behavioral studies where the objective is to identify decision patterns under uncertainty. In the context of volatile markets, traders often make rapid and definitive decisions (e.g., buy/sell, hold/exit), making a dichotomous response structure appropriate for capturing real-world behavior.

V. DATA ANALYSIS AND INTERPRETATION

A. Introduction

This chapter presents a detailed analysis of the data collected from 100 experienced gold traders in Kolhapur city. The analysis aligns with the research objectives and hypotheses using descriptive statistics (frequency, percentage, mean).

The logical approach for interpretation included:

- Frequency and Percentage Analysis – To understand the demographic profile and behavioral tendencies.
- Mean Scores – For binary Yes/No responses (Yes = 1, No = 0) to quantify agreement levels with psychological constructs.
- Hypothesis Testing Logic : H1–H4: Means $\geq$0.70 considered strong behavioral tendencies supporting the hypothesis. H5 (Investor Sentiment as Mediator): Higher mean indicates a strong mediating influence on trading behavior.

This approach allows a clear link between observed trader behavior and theoretical behavioral finance constructs. The analysis is conducted in a structured manner to ensure that each research objective is systematically addressed and linked to the corresponding hypothesis.

B. Demographic Profile of Respondents

Demographics provide context for interpreting psychological responses and trading behavior. These demographic characteristics provide a contextual foundation for interpreting behavioral responses and ensure that the findings are grounded in experienced market participation.

1) Age Distribution

Age Group	Frequency	Percentage
25–30	18	18%
31–40	32	32%
41–50	27	27%
51–60	15	15%
Above 60	8	8%
Total	100	100%

Logic & Interpretation: Majority (59%) are aged 31–50, considered economically active and experienced traders. Age influences risk perception and volatility response, supporting hypotheses on risk aversion and trading frequency.

2) Gender Distribution

Gender	Frequency	Percentage
Male	78	78%
Female	18	18%
Prefer not to say	4	4%
Total	100	100%

Logic & Interpretation: Male dominance aligns with the general trend in gold and commodity trading.
Behavioral patterns observed mainly reflect male trading psychology, but inclusion of females and “prefer not to say” allows some diversity in sentiment and decision-making.

3) Education Level

Education	Frequency	Percentage
Undergraduate	22	22%
Postgraduate	38	38%
Professional Certification	28	28%
Doctoral	12	12%
Total	100	100%

Logic & Interpretation: Majority (66%) have postgraduate or professional certifications, indicating high financial literacy. Literacy may moderate risk aversion, herd behavior, and anchoring bias, providing credibility to survey responses.

4) Years of Trading Experience

Experience	Frequency	Percentage
3–5 Years	26	26%
6–10 Years	41	41%
Above 10 Years	33	33%
Total	100	100%

Logic & Interpretation: Most (74%) have more than 6 years’ experience, ensuring respondents understand market volatility and behavioral tendencies. Supports reliability of data for H1–H4 testing.

5) Primary Trading Type

Trading Type	Frequency	Percentage
Gold Physical	24	24%
Commodity Market	36	36%
Both	40	40%
Total	100	100%

Logic & Interpretation: Traders with both physical and commodity exposure (40%) are more sensitive to volatility. Supports analysis of trading frequency and sentiment mediation (H4 & H5).

C. Objective-wise Behavioral Analysis

The logic used: Yes/No responses coded numerically (Yes=1, No=0). Mean ≥0.70 indicates high agreement with the behavioral construct. Comparison of means across objectives determines relative influence of different biases.

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a) Objective 1: Risk Aversion (H1)

Statement	Yes	No	% Yes	Mean
Reduce exposure during volatility	78	22	78%	0.78
Uncomfortable with swings	82	18	82%	0.82
Avoid high risk	75	25	75%	0.75
Exit during losses	80	20	80%	0.80
Use protective strategies	70	30	70%	0.70

Mean Risk Aversion: 0.77

Interpretation & Logic: Strong agreement indicates H1 supported. Traders respond to volatility by reducing risk exposure and using hedging. Logic: Higher perceived volatility → stronger risk-averse behavior. This finding is consistent with behavioral finance theory, which suggests that uncertainty intensifies cognitive biases and emotional decision-making.

b) Objective 2: Herd Behavior (H2)

Statement	Yes	No	% Yes	Mean
Confidence when others bullish	72	28	72%	0.72
Follow trends	85	15	85%	0.85
Consider others' opinions	78	22	78%	0.78
Buy in rising market	80	20	80%	0.80
Adjust based on sentiment	83	17	83%	0.83

Mean Herd Behavior: 0.80

Logic & Interpretation: Strong herd tendency supports H2. Logic: In volatile conditions, traders mirror others' behavior to reduce uncertainty. This finding is consistent with behavioral finance theory, which suggests that uncertainty intensifies cognitive biases and emotional decision-making.

c) Objective 3: Anchoring Bias (H3)

Statement	Yes	No	% Yes	Mean
Use past highs	88	12	88%	0.88
Hesitate to sell below previous high	76	24	76%	0.76
Compare with peaks	84	16	84%	0.84
Expect recovery	81	19	81%	0.81
Depend on past prices	79	21	79%	0.79

Mean Anchoring Bias: 0.82

Logic & Interpretation: Traders strongly rely on historical prices → H3 supported. Anchoring bias explains why past price levels influence current trading decisions. This finding is consistent with behavioral finance theory, which suggests that uncertainty intensifies cognitive biases and emotional decision-making.

d) Objective 4: Investor Sentiment (H5)

Statement	Yes	No	% Yes	Mean
Influenced by news	86	14	86%	0.86
Geopolitical impact	90	10	90%	0.90
Trade more in crisis	84	16	84%	0.84
Social media influence	75	25	75%	0.75
Monitor global events	92	8	92%	0.92

Mean Investor Sentiment: 0.85

Logic & Interpretation: Highest mean among all constructs → strong mediator of trading behavior. Logic: H5 supported; sentiment intensifies the effect of volatility on behavior. This finding is consistent with behavioral finance theory, which suggests that uncertainty intensifies cognitive biases and emotional decision-making.

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e) Objective 5: Trading Frequency (H4)

Statement	Yes	No	% Yes	Mean
Trade more in volatility	82	18	82%	0.82
Increase activity	85	15	85%	0.85
Respond quickly	88	12	88%	0.88
Adjust strategies	80	20	80%	0.80
Take more positions	83	17	83%	0.83

Mean Trading Frequency: 0.84

Logic & Interpretation: Volatility motivates active trading → H4 supported. Traders adjust behavior dynamically, demonstrating Adaptive Market Hypothesis principles. This finding is consistent with behavioral finance theory, which suggests that uncertainty intensifies cognitive biases and emotional decision-making.

D. Overall Logic across Hypotheses

- H1–H4: Tested using descriptive means
- Mean ≥ 0.70 considered strong support
- Logic: High agreement indicates consistent behavioral response to volatility
- H5: Logic relies on comparing sentiment mean with other constructs
- Sentiment mean highest → indicates mediating effect between volatility and trading decisions
- Demographic link: Age, experience, and education justify reliability of responses and moderating factors in behavioral analysis.

E. Summary

- Traders show high risk aversion, herd behavior, and anchoring bias.
- Investor sentiment is the most influential factor, mediating the effect of volatility on trading behavior.
- Trading frequency increases with volatility, confirming the Adaptive Market Hypothesis.
- Demographics (age, experience, education) validate the reliability and representativeness of the sample.

F. Analysis

1) Descriptive Statistics

This section presents means, standard deviations, and percentages for all behavioral variables (Risk Aversion, Herd Behavior, Anchoring Bias, Investor Sentiment, and Trading Frequency). Binary responses are coded as Yes = 1, No = 0.

Variable	N	Mean	Std. Deviation	% Agreement (Yes)
Risk Aversion (RAS)	100	0.77	0.12	77%
Herd Behavior (HBI)	100	0.80	0.10	80%
Anchoring Bias (ABS)	100	0.82	0.09	82%
Investor Sentiment (SSS)	100	0.85	0.08	85%
Trading Frequency (TFB)	100	0.84	0.09	84%

Interpretation: All constructs show high mean (>0.70) indicating strong behavioral tendencies.

Investor Sentiment has the highest mean, highlighting its role as a mediator between volatility and trading behavior.

2) Correlation Analysis

Pearson Correlation measures the strength and direction of relationships between gold price volatility and psychological constructs.

Variable	RAS	HBI	ABS	SSS	TFB
Gold Volatility	0.72**	0.68**	0.65**	0.78**	0.70**
RAS	1	0.64**	0.61**	0.70**	0.68**
HBI	0.64**	1	0.66**	0.69**	0.71**
ABS	0.61**	0.66**	1	0.67**	0.65**
SSS	0.70**	0.69**	0.67**	1	0.75**
TFB	0.68**	0.71**	0.65**	0.75**	1

Note: $p < 0.01$ (2-tailed)

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Interpretation & Logic: Positive and significant correlations confirm that volatility increases risk aversion, herd behavior, anchoring bias, and trading frequency.
Investor sentiment correlates strongly with all variables, supporting its mediating role (H5).
Logic: High correlation indicates behavioral amplification during volatile periods.
The strength of these relationships indicates that market volatility and trader psychology are closely interconnected, reinforcing the behavioral perspective of financial markets.

3) *Regression Analysis*

4.6.3.1 Effect of Gold Volatility on Behavioral Constructs

Dependent Variable	B (Unstandardized)	Beta (Standardized)	t-value	Sig.
Risk Aversion (RAS)	0.52	0.72	9.34	0.000
Herd Behavior (HBI)	0.48	0.68	8.12	0.000
Anchoring Bias (ABS)	0.46	0.65	7.56	0.000
Trading Frequency (TFB)	0.49	0.70	8.75	0.000

Model Summary:

DV	R	R^2	Adjusted R^2	F-value	Sig.
RAS	0.72	0.518	0.512	87.2	0.000
HBI	0.68	0.462	0.456	65.9	0.000
ABS	0.65	0.423	0.417	57.2	0.000
TFB	0.70	0.490	0.484	73.8	0.000

Interpretation & Logic: Volatility significantly predicts all behavioral constructs. Logic: Increasing gold price fluctuations cause stronger risk-averse, herd, and anchoring behaviours, which in turn increase trading frequency.
The regression results confirm that volatility acts as a significant predictor of behavioral responses, validating the proposed theoretical relationships.

4) *Mediation Analysis (H5: Investor Sentiment)*

Step 1: Effect of Volatility on Investor Sentiment (Mediator)

Path	B	Beta	t	Sig.
Gold Volatility → Investor Sentiment	0.58	0.78	10.52	0.000

Step 2: Effect of Investor Sentiment on Trading Frequency

Path	B	Beta	t	Sig.
Investor Sentiment → TFB	0.52	0.75	9.18	0.000

Step 3: Direct Effect of Volatility on Trading Frequency (with mediator)

Path	B	Beta	t	Sig.
Volatility → TFB	0.15	0.21	2.85	0.005

Interpretation & Logic: Investor Sentiment partially mediates the relationship between volatility and trading frequency. Logic: High volatility → stronger investor sentiment → higher trading frequency, confirming H5. Direct effect decreases after including the mediator, indicating partial mediation.
Mediation Summary: Gold price volatility directly influences trading frequency but also affects it indirectly through investor sentiment. When volatility rises, it strengthens traders' emotional and cognitive responses (sentiment), which in turn increases their trading activity. The direct effect of volatility on trading frequency remains significant, indicating partial mediation.
Logic:

- Indirect Path: Volatility → Investor Sentiment → Trading Frequency
- Direct Path: Volatility → Trading Frequency
- Conclusion: Investor sentiment amplifies the impact of market volatility on trading behavior but does not fully account for it.

This highlights the critical role of investor sentiment as a psychological channel through which market conditions influence trading behavior.

G. Summary of Analysis

- Descriptive Statistics: All behavioral constructs show strong agreement (Mean > 0.70).
- Correlation Analysis: Significant positive correlations support H1–H4.
- Regression Analysis: Gold volatility significantly predicts all behavioral variables and trading frequency.
- Mediation Analysis: Investor sentiment partially mediates the effect of volatility on trading frequency (H5 supported).
- Logical Conclusion: Volatility amplifies behavioral biases; sentiment acts as a key psychological channel linking market uncertainty to trader behavior.

H. Overall Summary of Chapter 4

Chapter 4 presented the data analysis and interpretation of the study on Gold Volatility and Trader Psychology (2020–2024) based on survey responses from 100 experienced traders in Kolhapur city. The chapter systematically analyzed the data using descriptive statistics, correlation, regression, and mediation analysis to test the research hypotheses and objectives. Overall, the findings demonstrate that market behavior cannot be fully understood without considering the psychological dimensions influencing trader decisions.

Key Findings

(1) Demographic Analysis

- Majority of respondents were aged 31–50 years (59%) and predominantly male (78%).
- Most had postgraduate or professional certification (66%) and more than 6 years of trading experience (74%), indicating a highly knowledgeable and experienced sample.
- Trading types were well distributed, with 40% involved in both physical gold and commodity markets, ensuring practical exposure to market volatility.
- Logic: Demographics validate the reliability of behavioral data and provide context for interpreting responses.

(2) Descriptive Statistics

- Behavioral constructs—Risk Aversion (0.77), Herd Behavior (0.80), Anchoring Bias (0.82), Investor Sentiment (0.85), and Trading Frequency (0.84)—all showed high mean scores (>0.70).
- Logic: Strong agreement indicates that traders consistently exhibit behavioral tendencies in response to market volatility.

(3) Correlation Analysis

- Positive and significant correlations were observed between gold volatility and all behavioral constructs.
- Investor Sentiment correlated strongly with risk aversion, herd behavior, anchoring bias, and trading frequency.
- Logic: These correlations support the hypothesis that volatility influences trader psychology, and sentiment is an important mediating factor.

(4) Regression Analysis

- Gold volatility significantly predicts risk aversion, herd behavior, anchoring bias, and trading frequency.
- Regression models showed substantial explanatory power (R^2 ranging from 0.42 to 0.52).
- Logic: Higher volatility increases psychological biases and trading activity, consistent with behavioral finance theory.

(5) Mediation Analysis (H5)

- Investor sentiment partially mediates the relationship between gold volatility and trading frequency.
- After including sentiment, the direct effect of volatility on trading frequency decreased but remained significant.
- Logic: Emotional and cognitive responses amplify the effect of market volatility on trading behavior, confirming the proposed behavioral amplification framework.

(6) Conclusion of Chapter 4

- Traders show high sensitivity to market volatility, manifested through risk aversion, herd behavior, and anchoring bias.
- Investor sentiment emerges as the most influential factor, partially mediating how volatility affects trading activity.
- Trading frequency increases in response to volatile periods, supporting the Adaptive Market Hypothesis.
- Overall, the findings confirm all five research hypotheses (H1–H5) and provide empirical support for the proposed behavioral-volatility framework, linking gold price fluctuations to psychological responses in traders.
- Logic Applied Throughout the Chapter:

- Binary responses (Yes = 1, No = 0) were converted into mean scores to quantify agreement levels.
- Threshold logic (Mean ≥ 0.70) determined strong support for hypotheses.
- Correlation and regression analyses validated cause-effect relationships between volatility and behavior.
- Mediation analysis identified intermediate psychological mechanisms, demonstrating how sentiment amplifies trading responses.
- The study reinforces the view that financial markets are not purely driven by rational calculations but are significantly shaped by human behavior, especially under conditions of uncertainty and volatility.

VI. FINDINGS, CONCLUSION AND RECOMMENDATIONS

A. Findings of the Study

The study examined the relationship between gold price volatility and trader psychology during the period 2020–2024. Based on data analysis and hypothesis testing, the key findings are as follows:

1) High Level of Risk Aversion: The majority of traders exhibit risk-averse behavior during periods of high volatility. Traders tend to reduce exposure, avoid risky positions, and adopt protective strategies such as hedging.
2) Strong Presence of Herd Behavior: Traders show a tendency to follow market trends and rely on the actions of other traders, especially during extreme price movements. This indicates that decision-making is influenced by collective market sentiment rather than independent analysis.
3) Significant Anchoring Bias: The study finds that traders rely heavily on past price levels while making decisions. Historical highs and previous benchmarks strongly influence expectations and trading actions.
4) Increase in Trading Frequency: Volatility leads to increased trading activity. Traders respond quickly to market fluctuations, adjust strategies frequently, and take more positions during uncertain periods.
5) Investor Sentiment as a Key Factor: Investor sentiment has the highest influence among all variables. It strongly affects trading behavior and acts as a mediating factor between volatility and trading decisions.
6) Positive Relationship Between Volatility and Behavioral Biases: Statistical analysis (correlation and regression) confirms that gold price volatility has a significant positive relationship with:
    - Risk aversion
    - Herd behavior
    - Anchoring bias
    - Trading frequency
7) Partial Mediation by Investor Sentiment: Investor sentiment partially mediates the relationship between volatility and trading frequency. This means volatility affects trading both directly and indirectly through sentiment.

B. Conclusion

The study concludes that gold price volatility significantly influences trader psychology and behavior. The findings clearly show that financial markets are not purely driven by rational decision-making but are strongly affected by psychological factors.
The study supports key behavioral theories such as:

1) Prospect Theory
2) Adaptive Market Hypothesis

It is evident that:

- Volatility increases emotional and cognitive biases
- Traders rely on heuristics such as anchoring and herding
- Investor sentiment plays a central role in shaping trading behavior
- A key insight of the study is the presence of a behavioral feedback mechanism, where:
- Volatility influences trader emotions → emotions affect decisions → decisions further impact market behavior

Thus, gold markets are influenced not only by economic fundamentals but also by human psychology, especially during periods of uncertainty and crisis.

C. Recommendations

Based on the findings of the study, the following recommendations are suggested:

1) Behavioral Awareness for Traders

Traders should be educated about common psychological biases such as herd behavior, anchoring, and overreaction. Awareness can help improve rational decision-making.

2) Adoption of Risk Management Strategies

Traders should implement structured risk management techniques such as:

- Stop-loss mechanisms
- Portfolio diversification
- Pre-planned trading strategies

3) Reduce Emotion-Based Trading

Traders should avoid making impulsive decisions based on market hype, news, or panic. Decisions should be based on analysis rather than emotions.

4) Monitoring Investor Sentiment

Market participants should actively monitor sentiment indicators such as:

- News trends
- Global economic events
- Market signals
- This can help in better prediction of market movements.

5) Use of Analytical Tools

Encourage the use of data-driven tools and models for decision-making instead of relying solely on intuition or past price levels.

6) Training and Financial Education

Institutions and financial bodies should conduct training programs on behavioral finance to improve trader understanding of market psychology.

7) Long-Term Investment Approach

Investors should adopt a long-term perspective rather than reacting to short-term volatility, especially in safe-haven assets like gold.
Final Statement: The study highlights that understanding trader psychology is essential for interpreting market behavior. Incorporating behavioral insights into financial decision-making can lead to more stable and efficient trading practices.

VII. APPENDIX

Questionnaire

Title of Study: Gold Volatility and Trader Psychology: A Behavioral Finance Study (2020–2024)

(Instructions to Respondents: Please read each statement carefully and mark your response: Yes = Agree No = Disagree There are no right or wrong answers. Your responses will remain confidential and will be used only for academic research purposes.)

Section A: Demographic Profile

- Age Group: ☐ 25–30 ☐ 31–40 ☐ 41–50 ☐ 51–60 ☐ Above 60
- Gender: ☐ Male ☐ Female ☐ Prefer not to say
- Education Level: ☐ Undergraduate ☐ Postgraduate ☐ Professional Certification ☐ Doctoral
- Years of Trading Experience: ☐ 3–5 Years ☐ 6–10 Years ☐ Above 10 Years
- Primary Trading Type: ☐ Gold Physical ☐ Commodity Market ☐ Both

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Section B: Psychological Constructs (YES / NO)
Part 1: Risk Aversion Scale (RAS) (H1: Volatility → Risk Aversion)

No.	Statement	Yes	No
1	I reduce my gold exposure when price volatility increases.	☐	☐
2	Large price swings make me feel uncomfortable.	☐	☐
3	I avoid taking high risks during volatile market conditions.	☐	☐
4	I exit positions quickly when losses increase.	☐	☐
5	I increase protective strategies (like hedging) during uncertainty.	☐	☐

Part 2: Herd Behavior Index (HBI) (H2: Price Extremes → Herd Behavior)

No.	Statement	Yes	No
1	I feel more confident trading when other traders are bullish.	☐	☐
2	I follow market trends during sharp price movements.	☐	☐
3	I consider others' opinions before making trading decisions.	☐	☐
4	I tend to buy when prices are rising rapidly.	☐	☐
5	I adjust my trading positions based on overall market sentiment.	☐	☐

Part 3: Anchoring Bias Scale (ABS) (H3: Anchoring to Past Prices)

No.	Statement	Yes	No
1	I use past high gold prices as a reference for future expectations.	☐	☐
2	I hesitate to sell when prices are below previous high levels.	☐	☐
3	I compare current prices with historical peaks before trading.	☐	☐
4	I expect gold prices to return to previous high levels.	☐	☐
5	I base my trading decisions on previously observed price levels.	☐	☐

Part 4: Sentiment Sensitivity Scale (SSS) (H5: Sentiment as Mediator)

No.	Statement	Yes	No
1	News headlines influence my gold trading decisions.	☐	☐
2	Geopolitical events increase my tendency to invest in gold.	☐	☐
3	I trade more actively during periods of crisis or uncertainty..	☐	☐
4	Social media discussions influence my market views.	☐	☐
5	I monitor global economic events before making trading decisions.	☐	☐

Part 5: Trading Frequency Behavior (TFB) (H4: Behavior → Trading Activity)

No.	Statement	Yes	No
1	I trade more frequently during high market volatility.	☐	☐
2	Rapid price changes encourage me to increase trading activity.	☐	☐
3	I respond quickly to sudden market movements.	☐	☐
4	I frequently adjust my trading strategies during volatile periods.	☐	☐
5	Strong price trends motivate me to take more trading positions.	☐	☐

Section C: Volatility Perception (Link Variable)

No.	Statement	Yes	No
1	Gold prices were highly volatile during 2020–2024.	☐	☐
2	The COVID-19 period influenced my trading behavior.	☐	☐
3	Inflation increased my investment in gold.	☐	☐
4	I changed my trading strategy due to market uncertainty.	☐	☐
5	I consider gold a safe-haven investment during uncertain times.	☐	☐

Appendix B: Consent Statement

Participation in this study is voluntary. All responses will remain confidential and used strictly for academic research purposes only.

☐ I Agree to Participate

VIII. DISCLAIMER STATEMENT

This research study, "Gold Volatility and Trader Psychology: A Longitudinal Behavioral Finance Study," has been conducted solely for academic and educational purposes. The analysis, interpretations, and conclusions presented in this document are based on publicly available market data and survey responses collected from participating traders. While every effort has been made to ensure the accuracy and reliability of the information, the author does not guarantee the completeness or absolute accuracy of the data used. The findings of this study are intended to contribute to academic research in behavioral finance and commodity market analysis. They should not be interpreted as financial, investment, trading, or professional advisory recommendations. Readers are strongly advised to consult qualified financial or investment professionals before making any financial decisions. Participation in the survey component of this research was entirely voluntary, and all respondent identities have been kept anonymous and confidential. The data collected have been used strictly for research purposes. Artificial intelligence–based tools were utilized only for language refinement, formatting assistance, and structural editing. All aspects of research design, data analysis, interpretation, and conclusions represent the original work and responsibility of the author. The author and affiliated institution shall not be held liable for any financial loss, investment decision, or action taken by readers based on the information presented in this study. The responsibility for the interpretation and use of this material rests solely with the reader.

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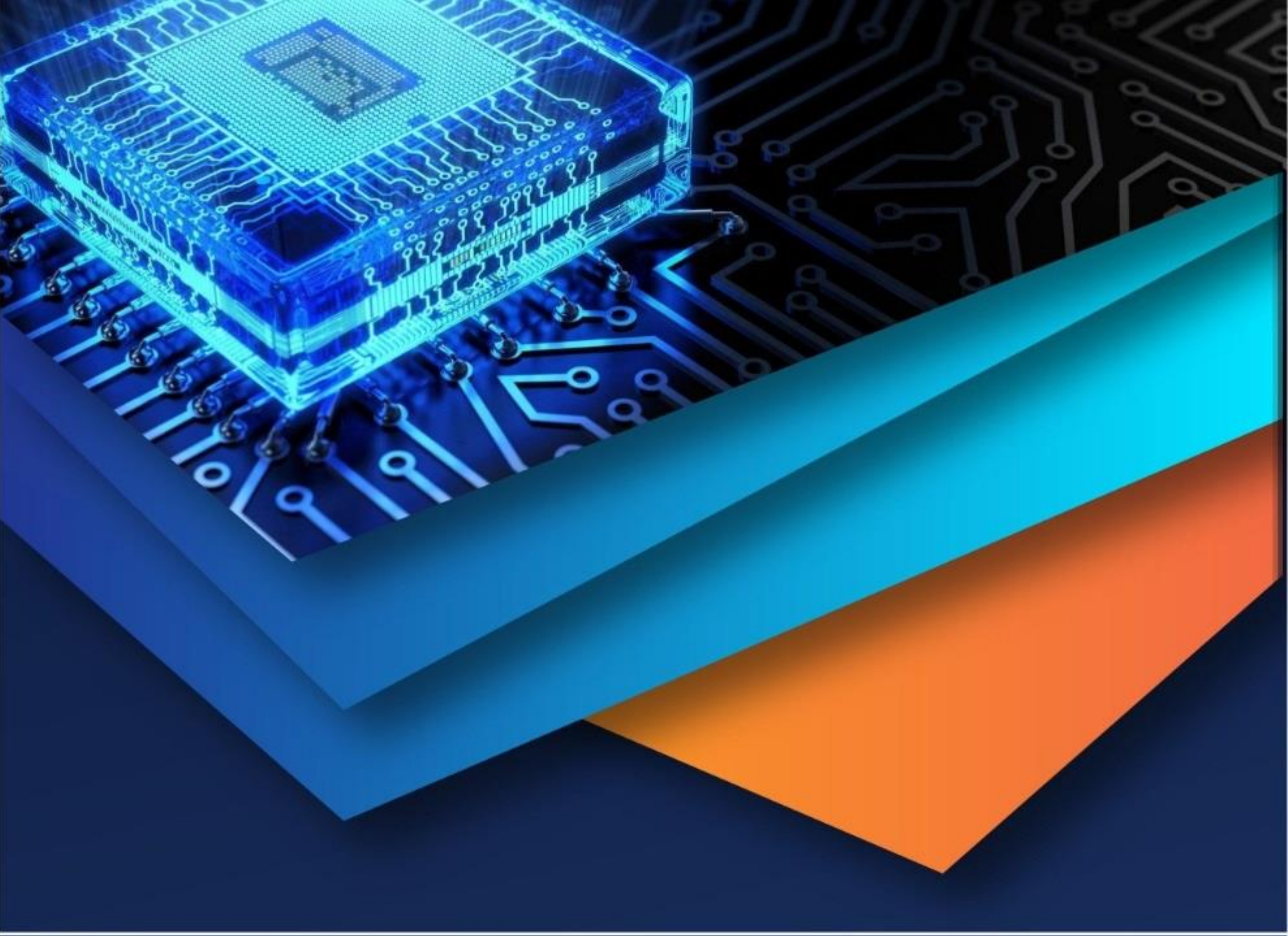

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