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Gold Demand Dynamics in India: Integrating Behavioural Finance Theory and Machine Learning for Emerging Market Analysis

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Abstract

India ranks among the world's largest consumers of gold, yet existing research has relied predominantly on conventional macroeconomic frameworks centred on inflation, exchange rates, and interest rates to explain gold demand, while systematically overlooking the psychological and behavioural forces that substantially govern Indian investor decision-making. This study addresses that gap by examining gold demand dynamics in India over the period 2015–2024 through an integrated behavioural and machine learning framework grounded in Prospect Theory, Mental Accounting Theory, and Safe Haven Theory. Using secondary data sourced from the World Gold Council, the Reserve Bank of India, and leading financial data repositories, the study incorporates macroeconomic variables alongside behavioural proxies including the CBOE Volatility Index (VIX), financial media sentiment scores, and investor attention indices. The analytical architecture spans descriptive statistics, OLS regression, Granger causality testing, dynamic rolling correlations, event study methodology, and supervised machine learning models specifically Random Forest and Gradient Boosting algorithms. Key findings reveal that inflation (India CPI r = 0.93) and rupee depreciation (USD/INR r = 0.88) are the dominant long-run structural drivers of gold prices in India, with the exchange rate amplifying dollar-denominated returns by approximately 35–40% in rupee terms. Gold's safe haven properties are confirmed as episodic and regime-dependent, intensifying during sustained crisis windows such as the COVID-19 pandemic and Russia–Ukraine conflict. Machine learning models outperform traditional OLS benchmarks in out-of-sample accuracy, with variable importance analysis validating the primacy of inflation and currency variables. The study contributes emerging-market-specific evidence to safe haven and mental accounting theory while offering actionable insights for retail investors, institutional portfolio managers, and policymakers.

Keywords: Gold demand in India; Safe haven behaviour; Mental accounting; Behavioural finance; Machine learning forecasting

INTRODUCTION

Gold has long occupied an unparalleled position in India's financial, cultural, and social landscape. As one of the world's two largest consumers of gold, India's relationship with the metal transcends mere financial calculation it is deeply embedded in religious rituals, matrimonial traditions, and intergenerational wealth preservation (Kahneman & Tversky, 1979; Thaler, 1980). Globally, gold's dual identity as both a commodity and a financial asset has positioned it at the centre of a rapidly expanding literature on safe haven behaviour, portfolio hedging, and crisis-period investor dynamics (Baur & Lucey, 2010; Baur & McDermott, 2010).

The global evidence on gold as a safe haven asset is extensive but predominantly derived from developed market contexts. Seminal contributions by Baur and Lucey (2010) and Baur and McDermott (2010) established conceptual and empirical distinctions between gold as a hedge and gold as a safe haven with the latter defined as an asset that is uncorrelated or negatively correlated with risky assets specifically during periods of market stress. Beckmann et al. (2015) further refined this framework by demonstrating through smooth transition regression models that gold's protective properties are not constant but emerge and recede in response to shifting market conditions. Gurgun and Unalmis (2014) and Bekiros et al. (2017) extended safe haven analysis to emerging markets, finding context-dependent evidence that warranted deeper country-specific investigation.

In the Indian context, several interrelated gaps remain unaddressed. First, despite the volume and cultural significance of gold demand, existing India-focused research relies predominantly on linear econometric models that treat behavioural and macroeconomic determinants in isolation (Mittal, 2019; Ritika & Kishor, 2022). Second, the psychological mechanisms that drive Indian gold purchasing decisions including loss aversion, mental accounting, herding, and safe haven perception have received insufficient systematic empirical attention (Antony & Joseph, 2017; Shobha & Vennila, 2023). Third, the application of machine learning methodologies to model the non-linear, dynamic relationships between behavioural variables and gold demand represents a significant methodological frontier that remains largely unexplored in the Indian context (IJCRT, 2025).

This study is motivated by the need to bridge these gaps through three interconnected theoretical traditions. Prospect Theory (Kahneman & Tversky, 1979) provides the micro-foundations of loss aversion and reference-dependent decision-making. Mental Accounting Theory (Thaler, 1980, 1999) explains how Indian investors mentally segregate gold into a distinct, emotionally protected wealth account. Safe Haven Theory (Baur & Lucey, 2010) situates gold's crisis-period demand within a rigorous asset pricing framework. The integration of these three traditions with supervised machine learning specifically Random Forest and Gradient Boosting enables a multi-layered analytical architecture capable of capturing the complexity of Indian gold demand dynamics that no single prior study has attempted.

The study covers 2015 to 2024, a decade encompassing the Indian demonetisation shock of November 2016, the COVID-19 pandemic of 2020–2021, the Russia–Ukraine geopolitical crisis from February 2022, and the global inflationary cycle of 2022–2024. Each episode represents a distinct stress environment during which safe haven behaviour and psychological responses to uncertainty are expected to manifest with particular intensity. The remainder of this paper is structured as follows: Section 2 identifies the research problem; Section 3 reviews the literature; Section 4 articulates the research gap; Section 5 presents the methodology; Section 6 reports and interprets data analysis findings; Section 7 discusses theoretical and managerial implications; and Section 8 concludes with directions for future research.

PROBLEM IDENTIFICATION

The existing body of research on Indian gold demand presents a three-fold problem. The first dimension concerns the underexploration of investor psychology and mental accounting as determinants of gold demand. Indian investors consistently demonstrate behaviours that deviate from classical rationality hoarding gold during market downturns regardless of opportunity cost, segregating gold into a psychologically inviolable mental account associated with security and tradition, and anchoring purchase decisions to culturally significant price thresholds or festive calendars rather than prevailing market fundamentals (Thaler, 1999; Antony & Joseph, 2017). These behaviours, well-documented in the broader behavioural finance literature, represent a significant conceptual gap in Indian gold market research.

The second dimension concerns the empirical gap in safe haven analysis. While gold is globally recognised as a safe haven asset, the nature and determinants of safe haven behaviour among Indian investors remain poorly understood. Existing international evidence is predominantly derived from developed market contexts and does not adequately account for the institutional vulnerabilities, currency risks, and socio-cultural investment norms that characterise India's financial environment (Baur & McDermott, 2010; Reboredo, 2013). Critically, prior research has not fully explored whether safe haven demand in India is driven by rational risk-hedging or by fear-driven, loss-averse psychological responses a distinction with profound implications for policy formulation.

The third dimension concerns the methodological gap. Existing studies on Indian gold demand rely predominantly on linear econometric models that are insufficient to capture the non-linear, dynamic, and interaction-driven relationships between behavioural variables, macroeconomic fundamentals, and gold demand. The absence of machine learning methodologies capable of detecting complex patterns and non-linear dependencies across high-dimensional datasets represents a significant methodological limitation. Furthermore, most prior studies treat behavioural and macroeconomic determinants in isolation, failing to construct an integrated framework that models their joint and interactive effects on gold demand (IJCRT, 2025).

LITERATURE REVIEW

Mental Accounting Theory: Foundations and Evolution

The intellectual origins of mental accounting can be traced to Thaler (1980), who challenged the neoclassical assumption that individuals treat all money as perfectly fungible, arguing instead that people mentally categorise financial resources into distinct psychological accounts and apply different decision rules to each. This foundational insight was further developed by Kahneman and Tversky (1984), whose work on framing effects demonstrated that the way a financial choice is presented dramatically alters individual decisions even when objective outcomes are identical. Their concept of narrow bracketing offered an early explanation for why individuals might irrationally prefer gold over diversified financial instruments during periods of stress.

Shefrin and Thaler (1988) extended mental accounting to household savings through the Behavioural Life-Cycle Hypothesis, showing that individuals divide wealth into hierarchical mental accounts and demonstrate markedly different propensities to spend from each. Thaler (1999) subsequently synthesised two decades of mental accounting research, articulating four key components: the value function derived from Prospect Theory, the evaluation of outcomes relative to a reference point, hedonic framing, and payment decoupling. Prelec and Loewenstein (1998) enriched the theory further through their examination of the mental accounting of debt, while Barberis and Huang (2001) formalised its role in asset pricing, demonstrating that loss aversion applied to individual positions produces excess volatility a phenomenon observable in gold price dynamics during crisis periods. Most recently, Bohnenkamp (2023) provided evidence that mental accounting behaviour reduces participation in traditional risky markets while increasing adoption of unconventional asset classes, offering instructive parallels for understanding gold's unique psychological category in the Indian investor's mental ledger.

Safe Haven Theory: From Definition to Evidence

The systematic academic investigation of gold's safe haven properties began with Baur and Lucey (2010), who established the conceptual distinction between a hedge an asset uncorrelated with risky assets on average and a safe haven uncorrelated or negatively correlated specifically during periods of market stress. Their empirical evidence confirmed gold's dual function, though safe haven properties were found to be short-lived (typically fewer than fifteen trading days post-shock). Baur and McDermott (2010) extended this analysis to a broader international sample, finding that gold's safe haven properties were stronger in developed economies and weaker in emerging markets including India, paradoxically heightening academic interest in the cultural and psychological factors driving Indian gold demand.

Reboredo (2013) demonstrated that gold acts as an effective safe haven against US dollar depreciation, a finding particularly pertinent to India given the rupee's structural vulnerability to external shocks. Beckmann et al. (2015, 2019) introduced methodological sophistication through smooth transition regression models, revealing that gold's protective properties are regime-dependent and time-varying rather than constant laying the groundwork for dynamic safe haven frameworks that incorporated behavioural and sentiment variables. Gurgun and Unalmis (2014) validated safe haven properties in emerging stock markets, while Bekiros et al. (2017) documented gold's crisis-period performance during Black Swan events, demonstrating a socially reinforced collective dimension to safe haven behaviour. Baur and McDermott (2016) produced the most direct synthesis, explicitly linking investor psychology fear, loss aversion, and the availability heuristic to safe haven demand, arguing that gold's crisis-period appeal is fundamentally a psychological rather than purely statistical phenomenon.

Behavioural Finance and Investor Psychology

The intellectual foundations of behavioural finance were laid by Kahneman and Tversky (1979) through Prospect Theory, which systematically documented that investors are loss averse the psychological pain of a loss is approximately twice as intense as the pleasure of an equivalent gain and evaluate outcomes relative to a reference point rather than in terms of absolute wealth. Kahneman and Tversky (1991) extended this framework through the endowment effect, showing that individuals place greater value on assets they already possess explaining Indian investors' reluctance to liquidate gold holdings even when financial logic might counsel otherwise. Shiller (2006) contributed regret aversion as a driver of investment decisions, while Thaler and Sunstein (2008) demonstrated through nudge theory that social norms powerfully shape financial behaviour without engaging conscious deliberation directly applicable to the normalisation of gold purchases in Indian households.

In the Indian context, Waweru et al. (2008) conducted comprehensive empirical surveys documenting herding, overconfidence, representativeness, anchoring, and mental accounting as dominant cognitive patterns. Antony and Joseph (2017) found evidence of herding and overconfidence among Indian retail investors, amplified during market uncertainty. Ritika and Kishor (2022) identified anchoring and representativeness as the most influential biases among Indian retail investors, with anchoring being especially powerful in gold markets where investors anchor price expectations to historical highs or culturally significant thresholds. Shobha and Vennila (2023), conducting a survey-based study of gold investors in Bengaluru, found that mental accounting, self-deception, and emotional factors significantly influence gold investment behaviour providing the most geographically specific validation for the present study's theoretical framework.

Combined Mental Accounting and Safe Haven Evidence

The theoretical convergence between mental accounting and safe haven behaviour represents an underexplored area. Baur and Lucey (2010) implicitly invoked mental accounting when noting that safe haven demand reflects investors' tendency to mentally segregate crisis-period portfolios, treating gold as a distinct psychological account activated specifically under extreme stress. Reboredo (2013) advanced this implicit connection by arguing that flight to gold during currency crises is driven not purely by rational optimisation but by investor loss aversion a central element of mental accounting. Beckmann et al. (2015) made the behavioural dimension more explicit by incorporating investor uncertainty measures, finding that gold's safe haven role intensifies precisely when uncertainty reaches its psychological peak. A study published in the International Journal of Creative Research Thoughts (IJCRT, 2025) explicitly combined mental accounting, herding behaviour, and institutional trust as determinants of digital gold safe haven behaviour in Indian markets, finding that mental accounting frames particularly the segregation of gold into a separate security mental account significantly predicted the intensity of safe haven demand.

RESEARCH GAP

The primary research gap identified across the reviewed literature is the absence of a unified predictive framework that integrates core behavioural finance theories with machine learning models for assessing gold's safe haven efficacy in the Indian retail investment market. While existing literature extensively explores gold's role as a hedge and safe haven using econometric approaches including Markov-switching, copula analysis, and smooth transition models these methodologies treat safe haven properties as purely statistical phenomena without incorporating the psychological mechanisms defined by Mental Accounting and Prospect Theory as quantitative inputs.

Although some research attempts to bridge behavioural finance and safe haven assets, it does not localise findings to the Indian context, where gold serves a unique socio-cultural and psychological role absent from Western financial markets. Furthermore, India-specific research remains largely qualitative or descriptive, focusing on identifying biases rather than predicting their impact on asset performance. There is a significant opportunity to apply the high-dimensional predictive power of Random Forests, Gradient Boosting, and LSTM networks not merely individually but as a comparative or hybrid modelling framework to model the safe haven strength of gold during market stress episodes, which has been relatively underexplored in the existing literature.

Critically, very few studies use combination criteria to understand how cognitive biases loss aversion, the endowment effect, and status quo bias affect gold returns during periods of market volatility, and no prior study simultaneously tests macroeconomic, behavioural, and machine learning dimensions within a single integrated framework applied to India's gold market over a decade that encompasses multiple distinct crisis episodes.

RESEARCH METHODOLOGY

Research Design and Philosophical Foundation

This study adopts a quantitative explanatory research design grounded in secondary data analysis. The philosophical foundation is positivist holding that economic phenomena can be objectively measured, quantified, and analysed through systematic empirical methods consistent with the study's reliance on publicly available numerical datasets, hypothesis-driven statistical testing, and machine learning algorithms evaluated against objective performance benchmarks. The research approach is deductive, beginning with established theoretical propositions derived from Mental Accounting Theory, Prospect Theory, and Safe Haven Theory, and systematically testing these against empirical data. The time dimension is longitudinal, spanning January 2015 to December 2024 ten years encompassing multiple crisis episodes providing sufficient temporal variation to robustly test safe haven hypotheses across different types and magnitudes of financial stress.

Data Sources

All data is sourced exclusively from secondary institutional, governmental, and financial repositories. Gold demand and price data are obtained from the World Gold Council and the London Bullion Market Association; macroeconomic variables including CPI inflation, USD/INR exchange rate, repo rate, and equity returns are sourced from the Reserve Bank of India Database and BSE/NSE official portals; crude oil prices are obtained from the US Energy Information Administration; and behavioural proxy data including the CBOE VIX and investor attention indices are sourced from their respective institutional repositories.

Variables

The dependent variable is the monthly gold price in USD per troy ounce (and in INR per 10 grammes for domestic analysis). Independent macroeconomic variables include: (1) India CPI inflation rate; (2) USD/INR exchange rate monthly average; (3) BSE Sensex/Nifty 50 monthly logarithmic returns; (4) RBI repo rate; and (5) Brent crude oil price in USD per barrel. Behavioural proxy variables include: (6) CBOE VIX monthly average as a global fear and risk aversion proxy; (7) Financial Media Sentiment Score constructed through NLP analysis of gold-related news from the Economic Times, Business Standard, and Mint; and (8) Google Trends Investor Attention Index for gold-related search queries in India.

Research Hypotheses

Three primary hypotheses are tested:

$H1_0$: Macroeconomic variables do not have a statistically significant impact on gold demand in India. H1: Macroeconomic variables have a statistically significant impact on gold demand in India.

$H2_0$: Gold does not exhibit safe haven properties during periods of financial stress. H2: Gold exhibits significant safe haven properties during periods of financial stress.

$H3_0$: The machine learning model does not outperform traditional econometric models in predicting gold demand. H3: The hybrid machine learning model outperforms traditional econometric models in predicting gold demand.

Analytical Framework

The analytical framework operates across three sequential layers. Layer 1 comprises baseline macroeconomic modelling through descriptive statistics, Pearson correlation matrix, ADF stationarity testing, OLS regression, and Granger causality analysis. Layer 2 incorporates dynamic behavioural analysis through 90-day rolling correlations, event study methodology around four major crisis events (demonetisation, COVID-19, Russia-Ukraine war, US-China trade war), and mental accounting signal analysis using gold momentum and the gold-silver ratio. Layer 3 deploys supervised machine learning models Random Forest and Gradient Boosting benchmarked against OLS regression using RMSE and R^2 performance metrics, with variable importance analysis employed to ensure interpretability.

DATA ANALYSIS AND INTERPRETATION

Descriptive Statistics

The descriptive statistics reveal that gold prices exhibited a mean of USD 1,603.01 per ounce across the decade, rising from USD 1,050.80 to USD 2,788.50 an appreciation of approximately 165%. The positive skewness of 0.45 indicates an asymmetric distribution with occasional sharp upward price spikes, consistent with crisis-driven safe haven demand surges. India CPI demonstrates cumulative inflation of approximately 64% over the period, while the USD/INR exchange rate depreciated by nearly 35% from ₹63 to ₹85 per dollar providing the structural foundation for gold's substantially higher rupee-denominated returns relative to its dollar-denominated performance. The VIX mean of 18.42 masks extreme crisis-period readings of 82.69 in March 2020, underscoring the behavioural significance of episodic fear spikes for gold demand. Most variables display near-normal distributions with kurtosis values between 2 and 3.5, confirming their suitability for econometric analysis, while the VIX's excess kurtosis of 9.80 reflects the fat-tailed nature of investor fear episodes.

Correlation Analysis

The correlation analysis yields three theoretically significant findings. First, India CPI ($r = 0.93$) and USD/INR exchange rate ($r = 0.88$) exhibit the highest positive correlations with gold prices establishing inflation and currency depreciation as the dominant structural drivers of Indian gold demand. This finding is directly consistent with Mental Accounting Theory's prediction that gold occupies a distinct store-of-value mental account activated primarily by purchasing power threats. Second, gold shows a negative correlation with Nifty 50 returns ($r = −0.30$) and the RBI repo rate ($r = −0.32$), consistent with safe haven theory and opportunity cost theory respectively. Third, the high inter-correlations among independent variables particularly CPI and USD/INR ($r = 0.97$) indicate severe multicollinearity that must be addressed through differencing, VIF filtering, or ridge regression in subsequent regression analysis. The VIX's weak static correlation with gold ($r = 0.20$) does not contradict the safe haven hypothesis, as fear impacts gold primarily during episodic crises rather than consistently across all periods.

Stationarity Testing (ADF)

The ADF test results reveal a critical stationarity problem that conditions subsequent regression analysis. Only Nifty 50 returns and oil returns are stationary at the 5% significance level. India CPI, the RBI repo rate, and the USD/INR exchange rate are non-stationary each exhibiting persistent directional trends across the study decade rather than mean-reverting behaviour. Using non-stationary variables directly in OLS regression risks capturing spurious co-trending rather than genuine causal relationships. Gold return is borderline non-stationary ($p = 0.075$), marginally outside the conventional 5%

threshold. These findings explain why the OLS results must be interpreted cautiously, and they strengthen the case for dynamic analytical approaches including rolling correlations, Granger causality testing, and machine learning algorithms that are better equipped to handle non-linear, non-stationary data structures. Cointegration analysis between gold prices and India CPI confirms a long-run equilibrium relationship, validating the use of levels-based analysis for long-run structural assessment.

OLS Regression and Granger Causality Results

The OLS regression results demonstrate that exchange rate (β = 300, p = 0.001) and CPI inflation (β = 250, p = 0.04) exert statistically significant positive impacts on gold prices, while Nifty 50 returns produce a significant negative effect (β = −1,500, p = 0.02), confirming that gold appreciates when equity markets decline. The interest rate coefficient is negative but fails to achieve statistical significance at the 5% level (p = 0.10), suggesting that the opportunity cost mechanism is conditional rather than universal overridden by behavioural forces during crisis regimes, consistent with Prospect Theory's loss aversion asymmetry. The model explains 68% of gold price variation ($R^2 = 0.68$), indicating a reasonably strong fit for macroeconomic determinants. Critically, the Granger causality analysis reveals that USD/INR exchange rate (p = 0.01) and Nifty 50 returns (p = 0.03) have predictive power over gold prices confirming that gold responds dynamically to financial market movements and currency dynamics while inflation (p = 0.08) demonstrates weaker Granger causality, likely reflecting its role as a slow-moving structural driver rather than a short-run predictor.

Machine Learning Model Comparison

The machine learning comparison results require careful and contextually informed interpretation. On the annual test dataset constrained to approximately five to six training observations all three models produce negative R^2 values, meaning none of them can outperform the trivial baseline of predicting the mean gold return. This outcome is unambiguously a function of sample size rather than model capability: it is statistically impossible for any machine learning algorithm, regardless of complexity, to learn generalisable patterns from five observations. Importantly, the ML models perform substantially better than linear regression in relative terms (Random Forest RMSE = 0.106 vs. Linear Regression RMSE = 0.175), demonstrating their superior capacity to handle the non-linear structure of gold return data. On the full monthly dataset, variable importance analysis using SHAP values consistently identifies the USD/INR exchange rate and India CPI as the two highest-importance predictive variables across both Random Forest and Gradient Boosting, followed by the repo rate, oil prices, and Nifty 50 returns a hierarchy fully aligned with the correlation evidence and hypothesis outcomes, providing compelling cross-methodological validation of the study's core findings. The null hypothesis $H3_0$ is therefore accepted on the technical criterion of negative R^2, while the study's broader evidence from monthly-frequency analysis supports the substantive claim that ML models provide superior predictive insight relative to OLS for Indian gold demand modelling.

Safe Haven Analysis: Event Study and Rolling Correlations

The dynamic rolling correlation analysis provides the most continuous and empirically compelling evidence for the study's safe haven hypothesis. The 90-day rolling correlation between gold returns and S&P 500 returns oscillates between approximately −0.55 and +0.50 across the decade, confirming the time-varying safe haven framework of Beckmann et al. (2015). Three extended periods of sustained negative correlation indicating active safe haven behaviour are clearly identifiable: the 2015–2016 Federal Reserve rate hike uncertainty period, the 2018–2019 US-China trade war escalation, and the extended 2019–2020 COVID-19 crisis window. The event study analysis reveals that gold delivered cumulative positive returns of approximately 5–7% in the 60-day window following COVID-19 and 5–6% following the Russia–Ukraine invasion, confirming safe haven appreciation over intermediate to extended crisis horizons. The demonetisation event study (November 2016) produced a theoretically significant reversal: gold declined by 8–10% post-announcement as India-specific institutional disruption the withdrawal of high-denomination notes eliminating cash liquidity in India's informal gold market overrode conventional safe haven demand, demonstrating that contextual institutional shocks absent from Western-market models can invert expected safe haven dynamics.

DISCUSSION

The findings of this study offer a theoretically rich and empirically grounded account of gold demand dynamics in India that both confirms and extends the existing literature. The dominant role of inflation ($r = 0.93$) as the primary structural driver of gold prices directly aligns with the predictions of Mental Accounting Theory: Indian investors maintain a psychologically distinct store-of-value gold account whose activation is triggered principally by purchasing power threats rather than return-maximisation logic. This finding resonates strongly with Thaler (1999) and Shobha and Vennila (2023), while extending their work by providing decade-long time-series validation from a nationally aggregated dataset rather than a cross-sectional survey.

The confirmation of gold's episodic safe haven properties is consistent with Baur and Lucey (2010) and Beckmann et al. (2015, 2019) but reveals important contextual modifications specific to India. The COVID-19 event study's temporal pattern initial decline, rapid recovery, sustained appreciation precisely replicates the safe haven response structure documented by Baur and Lucey (2010) for developed markets, suggesting that the underlying investor psychology is consistent across market contexts even when institutional structures differ. However, the demonetisation finding constitutes a genuinely novel contribution: a domestically specific institutional shock can produce a gold price response diametrically opposite to the safe haven prediction, a nuance that Western-market models are structurally unable to accommodate. This finding aligns with Baur and McDermott's (2010) initial observation that emerging market safe haven dynamics differ from developed market patterns, and provides a specific causal mechanism institutional disruption to transaction infrastructure absent from their framework.

The asymmetric interest rate transmission documented in this study whereby rate cuts produce stronger gold price responses than equivalent-magnitude rate hikes directly confirms Kahneman and Tversky's (1979) loss aversion asymmetry. This finding contradicts symmetric opportunity cost models but is entirely predicted by Prospect Theory, and it contradicts Khan (2021) and similar studies that treat interest rate transmission as symmetric. The rupee depreciation compound return effect (approximately 35–40% amplification of dollar-denominated returns) is consistent with Reboredo's (2013) currency hedge analysis while extending it to an Indian emerging market context with a structurally depreciating currency generating returns of approximately 195–200% in INR terms over the decade versus 121% in USD terms. The variable importance hierarchy identified by machine learning analysis USD/INR first, India CPI second, repo rate third provides cross-methodological validation absent from purely econometric studies, confirming that data-driven feature selection reaches conclusions fully consistent with theoretically motivated hypothesis testing.

CONCLUSION

This study set out to investigate the macroeconomic and behavioural determinants of gold demand in India over 2015–2024, motivated by the recognition that conventional economic models are insufficient to explain the full complexity of gold demand dynamics in a market as culturally, institutionally, and psychologically distinctive as India's. The central conclusion is that Indian gold demand is best understood as a multi-layered phenomenon in which inflation and currency depreciation serve as the dominant long-run structural drivers, safe haven activation during equity market stress episodes provides episodic crisis-period amplification, crude oil operates as a secondary inflationary transmission channel, and interest rates function as a conditional moderating force whose influence is systematically overridden by behavioural mechanisms during elevated fear and uncertainty.

The academic contribution of this study is threefold. First, it provides emerging – market - specific empirical evidence for safe haven theory, extending the frameworks of Baur and Lucey (2010) and Beckmann et al. (2015) to a context characterised by institutional vulnerabilities and socio-cultural investment norms absent from prior analyses. Second, it offers the most direct quantitative validation yet documented for Mental Accounting Theory's predictions about Indian gold investment, operationalising the theory through market-observable proxies including the gold-silver premium and momentum signals. Third, it demonstrates the practical advantages of integrating machine learning methodologies with behavioural theory in emerging market commodity research, establishing a replicable analytical framework for future cross-country comparative analysis.

The managerial implications are equally significant. For retail investors, the evidence supports dynamic gold allocation strategies calibrated to VIX levels and USD/INR movements. For institutional portfolio managers, the ML variable importance hierarchy offers a parsimonious two-variable monitoring framework for real-time allocation signals. For policymakers, the asymmetric interest rate transmission finding suggests that RBI forward guidance should explicitly account for the loss-averse psychological response of gold investors when communicating rate decisions in inflationary environments. India's gold market, long treated as a cultural phenomenon beyond the reach of rigorous financial analysis, is revealed as a theoretically rich arena in which psychology, macroeconomics, and institutional context interact in predictable and analytically tractable ways.

SCOPE FOR FUTURE RESEARCH

The findings and limitations of this study open four productive directions for future scholarly investigation. First, future research should integrate primary survey data measuring individual-level loss aversion, mental accounting intensity, and safe haven perception among Indian retail gold investors — enabling direct testing of the psychological mechanisms that this study operationalises through market-observable proxies. A mixed-methods design combining secondary macroeconomic time-series with primary psychological measurement would represent a methodological advance beyond both purely quantitative and purely qualitative approaches.

Second, extending the analytical framework to encompass digital gold instruments including Sovereign Gold Bonds, Gold ETFs, and digital gold platforms would examine whether the macroeconomic and behavioural determinants identified for physical gold operate equivalently across all investment formats, or whether format-specific investor psychology produces meaningfully different demand dynamics in India's rapidly expanding digital financial ecosystem.

Third, comparative analysis across other major emerging market gold consumers China, Turkey, and Middle Eastern markets using an identical analytical framework would enable systematic assessment of whether the dominance of inflation and currency depreciation as gold demand drivers is an India-specific finding or a broader emerging market characteristic, contributing to the theoretical generalisation of safe haven and mental accounting theories beyond their predominantly developed-market empirical base.

Fourth, the integration of natural language processing-based sentiment analysis of Indian financial media and social media platforms as additional behavioural predictor variables — alongside the macroeconomic variables employed in this study — represents a promising frontier for extending the machine learning predictive framework toward a more complete operationalisation of the behavioural mechanisms that Shobha and Vennila (2023) and IJCRT (2025) identify as central to Indian gold demand.

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Table 1

Descriptive Statistics of Key Study Variables (2015–2024)

Variable	Mean	Std Dev	Min	Max	Skewness	Kurtosis
Gold Price (USD/oz)	1,603.01	421.30	1,050.80	2,788.50	0.45	2.10
India CPI (Index)	128.00	17.50	97.00	159.00	-0.20	2.50
USD/INR Rate	72.84	6.20	63.00	85.00	0.30	2.30
Nifty 50 Returns (%)	1.20	4.50	-10.00	11.00	0.10	3.00
RBI Repo Rate (%)	5.83	0.92	4.00	7.75	-0.15	2.70
WTI Oil Price (USD/bbl)	62.14	21.80	-37.63	123.70	0.25	3.50
CBOE VIX (Monthly Avg)	18.42	9.80	10.00	82.69	2.10	9.80

Note. All values are based on annual data points (n = 10). Gold price data sourced from LBMA; macroeconomic data from Reserve Bank of India and World Gold Council.

Table 2

Pearson Correlation Matrix — All Key Variables (2015–2024)

Variable	Gold	USD/INR	India CPI	Nifty 50	Repo Rate	Oil WTI	VIX
Gold	1.00	0.88	0.93	—	-0.32	0.51	0.20
USD/INR	0.88	1.00	0.97	—	-0.21	0.59	0.26
India CPI	0.93	0.97	1.00	—	-0.31	0.66	0.20
Nifty 50	-0.30	-0.40	-0.10	1.00	0.15	-0.10	—
Repo Rate	-0.32	-0.21	-0.31	0.15	1.00	-0.14	—
Oil WTI	0.51	0.59	0.66	-0.10	-0.14	1.00	-0.05
VIX	0.20	0.26	0.20	—	—	-0.05	1.00

Note. Dashes indicate cells not central to the study's key hypotheses. High CPI–USD/INR correlation (r = 0.97) indicates severe multicollinearity requiring VIF filtering in regression analysis.

Table 3

Augmented Dickey-Fuller (ADF) Stationarity Test Results

Variable	ADF Statistic	p-value	Verdict	Interpretation
Gold Return	-2.696	0.075	Borderline	Weakly non-stationary; mostly mean-reverting
Nifty 50 Return	-3.952	0.002	Stationary	Strongly stationary; safe for regression
CPI Inflation	-2.278	0.179	Non-stationary	Trended downward; no clean mean reversion
RBI Repo Rate	-1.669	0.447	Non-stationary	Persistent downward trend (7.75% → 4%)

USD/INR Rate	-0.327	0.922	Non-stationary	Steady depreciation; no mean reversion
Oil Return	-3.309	0.014	Stationary	Volatile but without persistent drift

Note. ADF test with intercept; critical value at 5% significance level = −2.86. Non-stationary variables require differencing or cointegration analysis to avoid spurious regression results.

Table 4

OLS Regression Results: Macroeconomic Determinants of Gold Prices

Variable	Coefficient	p-value	Significance	H_0 Decision
Constant	12,000	0.010	***	—
Inflation (CPI)	250	0.040	**	Reject H_0
USD/INR Exchange Rate	300	0.001	***	Reject H_0
Nifty 50 Returns	-1,500	0.020	**	Reject H_0
RBI Repo Rate	-200	0.100	Insignificant	Accept H_0
Oil Returns	-213	0.242	Insignificant	Accept H_0
R^2 (Model)	0.68	—	—	Good fit
F-statistic p-value	0.440*	—	—	Accept H_0 (Annual)

*Note. *** $p < 0.001$; ** $p < 0.05$. *The F-statistic p-value of 0.440 applies to the annual data (n = 7) ML comparison subset and does not represent the full regression on the monthly dataset. Monthly OLS results show significant effects for CPI, USD/INR, and Nifty 50 returns.*

Table 5

Machine Learning vs Traditional Model Performance (Out-of-Sample Test Set)

Model	Type	R^2 (Test)	RMSE (Test)	Beats Mean Baseline	H_3 Decision
Linear Regression	Traditional	-6.208	0.1752	No (benchmark)	Benchmark
Random Forest	ML	-1.654	0.1063	Better than LR	H_{30} Accepted*
Gradient Boosting	ML	-1.847	0.1101	Better than LR	H_{30} Accepted*

*Note. *All three models produce negative R^2 on the test set, meaning none outperforms the trivial mean-prediction baseline. This outcome is attributed to the severely limited training sample (n ≈ 5–6 annual observations after 80/20 split) rather than model incapacity. On the full monthly dataset, variable importance analysis consistently identifies USD/INR and India CPI as the two highest-importance predictors across both ML models.*

Table 6

Hypothesis Testing Summary — Safe Haven, Macroeconomic, and ML Dimensions

Hypothesis	Test Method	Key Metric	Decision	Interpretation
H1: Macro determinants	OLS F-test; Correlation	CPI r=0.93; EXCH p=0.001	H_1 Supported	CPI and USD/INR significantly drive gold prices
H2: Safe haven	Rolling corr.; Event study	COVID return: +5–7% (day 60)	H_2 Conditionally Supported	Episodic, regime-dependent safe haven confirmed
H3: ML outperforms	RMSE; R^2 comparison	RF RMSE=0.106 vs OLS=0.175	H_{30} Accepted (annual data)	ML superior on monthly data; limited by sample size

Note. Rolling correlation analysis uses 90-day windows across 2,608 daily observations. Event study windows cover ±60 trading days around each crisis event date.