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AI-DRIVEN BEHAVIORAL ECONOMICS IN EMERGING MARKETS: MODELING INVESTOR BIASES AND MARKET ANOMALIES IN NEPAL'S STOCK EXCHANGE (NEPSE)

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ABSTRACT

Artificial Intelligence (AI) is having a notable impact on global capital markets, influencing everything from transactions to investor behavior.The convergence of AI and behavioral economics is becoming a defining force in global capital markets, impacting both transaction dynamics and investor behavior. However, the emerging markets like the Stock Exchange of Nepal (NEPSE) are still relatively under-researched in this joint space where informational asymmetries exist, there is not enough institutional investor participation and regulation is fragmented and subject to cognitive biases. This study involves the application of machine learning, natural language processing (NLP), and structural equation modeling (SEM/PLS- SEM) to primary investor survey data as well as secondary NEPSE market indices to detect, measure, and mitigate biases of investors associated with anomalies in the NEPSE market using AI driven analytical models. A sequential explanatory mixed method was used. The questionnaire, consisting of a 5-point Likert scale questionnaire and semi-structured interviews with 22 active NEPSE institutional experts, were used to collect the quantitative data from 547 active investors in NEPSE. The secondary data consisted of day-to-day returns of NEPSE index from 2019-2025. Results confirm that overconfidence bias (beta = 0.431, $p < 0.001$), herding behavior (beta = 0.389, $p < 0.001$), loss aversion (beta = 0.312, $p < 0.001$), and anchoring bias (beta = 0.278, $p < 0.01$) significantly predict suboptimal investment decisions. The accuracy of investor sentiment classification achieved by the AI-based sentiment analysis with the BERT model is 91.7%. There is a moderation effect between herding and investment decisions when introducing the use of AI and a partial mediation of the relation of herding and loss aversion effect when introducing financial risk propensity.The use of AI in herding and the use of financial

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risk propensity partially mediate the relationship between herding and loss aversion. NEPSE shows non-random distribution and time varying inefficiency which is consistent with the premise of the Adaptive Market Hypothesis (AMH). It is a study that combines the AI model of behavioral econometrics with direct psychology data of investors from the primary market to Nepal, and proposes a Behavioral Anomaly Detection Framework (BADF) combining the elements of Prospect Theory, Adaptive Market Hypothesis, and Human centered AI Design Principles.

Keywords: *behavioral finance; investor biases; market anomalies; Nepal Stock Exchange; NEPSE; artificial intelligence; machine learning; emerging markets; Adaptive Market Hypothesis; herding behavior*

1. INTRODUCTION

1.1 Global Context: The Convergence of AI and Behavioral Finance

Over the past ten years, artificial intelligence (AI), digital financial transformation and behavioural economics have converged in a geologic moment to become a true game-changer for the global capital markets. The adoption of Industry 5.0 principles, which is not only about automation but also a combination of human and machine elements, real-time decision assistance and data-driven intelligence has ushered financial market analysis into the 21st century (Carayannis et al., 2022). As of 2025, the global financial services industry has invested over USD 130 billion in AI, with machine learning (ML) and natural language processing (NLP) models integrated in various areas such as trading platforms, risk management systems, and advisory services for retail investors (World Economic Forum, 2024). At the same time, behavioural finance is capturing the regulatory and academic focus as the retail investor gradually becomes a dominant part of emerging capital markets. Structurally, traditional finance theory, which is built around the rational agent paradigm and the Efficient Market Hypothesis (EMH) is very limited in its ability to explain the patterns of systematic irrationalities observed in markets with information asymmetries, weak regulation and low financial literacy (Thaler, 2015; Barberis & Thaler, 2003). There has also been a more firmly empirical approach to the investor psychology problem that has been introduced by behavioral economics as derived from Kahneman and Tversky (1979) Prospect Theory and later works of the heuristics and cognitive bias literature. However, the application of AI-powered computational approaches in behavioural economic modelling is still a fledgling area, especially of emerging markets (Maheshwari et al., 2025; Ullah et al., 2026). The Nepal Stock Exchange (NEPSE) offers an extremely intriguing and un-studied empirical field for this study. Since its inception in 1993, NEPSE has seen a tantalizing rise in retail trading investor participation since the digital dematerialization reforms (2015-2017) and the post-COVID days of speculation (2020-2021) when the index has climbed from around 1200 points to over 3200 points, luring millions of trading investors with minimal financial knowledge. There are 238 companies with the market capitalization of above NPR 3.2 trillion listed in NEPSE as of now, which still show signs of being a frontier-tier emerging market—they are thinly liquid, have a concentrated allocation of sectors, particularly banking, limited derivative instruments and have a marked tendency to experience “herd-driven” price volatility (Securities Board of Nepal [SEBON], 2024).

1.2 Research Problem and Identified Gaps

Some key research questions arise from the interplay between AI, behavioural economics and NEPSE. Practically speaking, the clutch of typically retail investors, who are little to no aware of formal financial education, commonly display investment behavior patterns that create inefficiency in markets and personal losses: over-confidence, herd mentality, loss aversion and anchoring. There is no formal nor an AI driven process for real-time detection, modelling, and communication of these biases to the investor or regulator. Secondly, theoretical, empirical, contextual, and methodological gaps exist. To date, the use of prospect theory in conjunction with the adaptive market hypothesis (Lo, 2004) has not been investigated so far in the context of NEPSE in AI-mediated situation. Empirically, the relatively few existing studies (e.g., Sharma & Adhikari, 2024; Pathak et al., 2024) are conducted cross-sectionally, using one method of data collection and do not combine machine learning data with behavioral survey data. In relation to market structures, there are also certain aspects in which Nepal has a different structure from the South Asian markets (South Asian countries like India, Pakistan and Bangladesh) as the market is not supported with algorithmic trading, the demographic of the investors is also different, and regulatory problems also provide a huge difference. In terms of methodology, none of the study has used the PLS-SEM and AI-moderation analysis to NEPSE data.

1.3 Research Objectives and Questions

The key objectives of this study are to identify the prevalence of an investor's various behavioral biases such as Overconfidence bias, Herding bias, Loss aversion, Anchoring bias, and Regret aversion among NEPSE investors, to test if such investor's behavioral biases create financial market anomalies or inefficiencies in the NEPSE indices, to develop and validate an AI Based Behavioral Anomaly Detection Framework (BADF) using machine learning and natural language processing (NLP) based sentiment analysis and analysis of how the adoption of AI moderates the associations between investor's behavioral biases and their investment decisions and whether financial risk propensity mediates the relationships between the investor's behavioral bias and investor's investment decision. Similarly four research questions are raised: RQ1: What is the extent of the prediction made by cognitive biases (overconfidence, herding, loss aversion, anchoring, regret avoidance) for sub-optimal investment decision in NEPSE? RQ2: Whether the market efficiency of NEPSE supports Adaptive Market Hypothesis or not and what are the anomalies which are statistically persistent? Card4: What is the accuracy of AI / ML sentiment analysis models on the classification of investor sentiment of NEPSE from textual and social media data? RQ4: Does adoption of AI behaviours reduce effect of behavioural biases on investment decisions?

1.4 Contributions of the Study

This research can benefit and contribute in four categories. In theory, it adds an emerging market behavioral framework based on the AI Augmented version of both the theories: Prospect Theory and Adaptive Market Hypothesis, and makes it a potentially testable model. It is an empirical dataset of mixed method and AI-integrated behavioural finance data for NEPSE over the period 2019-2025. In practice, it provides investors with actionable recommendations, investment advisors for brokers, and regulations suggestions, all informed by AI-identified trends of bias. From a policy perspective, it provides guidance to SEBON's regulatory reform program with respect to market microstructure conditions which can exacerbate behavioral anomalies and cannot be easily fixed without transparency mechanisms that are facilitated by AI.

2. LITERATURE REVIEW

2.1 Behavioral Finance: Foundations and Constructs

Behavioral finance grew out of the less-then-perfect predictions of the neoclassical rational-agent models of investor behavior documented in the literature (Kahneman & Tversky, 1979; Thaler & Sunstein, 2008). The basic Prospect Theory is the theory that investors compare expected gains and losses against some reference point and are loss averse (the pain of the loss is more severe than that of an equivalent gain), and that they have decreasing sensitivity to gains and losses leading to asymmetric utility functions that can account for systematic deviations from expected utility maximizing behavior. Behavioral finance was then put on a sound footing to account for market anomalies in subsequent research by Shefrin and Statman (1985), Jegadeesh and Titman (1993), and De Bondt and Thaler (1985). There are five main constructs of cognitive factors that are of importance in this study. The tendency to think that they know more, can predict more and have more control over events is consistently found to be the most far-reaching and deadly problem in equity markets (Barber & Odean, 2001). If everyone buys or sells according to the compromise of the other investors or markets, even when there is privately held information, there are high potential for momentum crashes and bubble formation – this is known as herd behavior (Bikhchandani et al., 1992). The tendency to overvalue potential losses compared to gains, codenamed “loss aversion,” produces biases of holding on to winners and exiting losers. Anchoring bias occurs when there is excessive reliance on a first reference price or piece of information used to update beliefs and these update beliefs in a manner that distorts the fair valuation of the price or beliefs. Regret aversion is what causes over-optimization of conversion and a tendency to "change one's mind" because a particular conversion attempt (candidate) was not successful and post decision regret ensued.

2.2 Evidence from Emerging Markets

In recent years the literature of behavioral finance has begun to focus on investor psychology in emerging markets (EMs) throughout Asia and South Asia. Cognitive bias frameworks are relevant outside of developed economies as overconfidence and representative heuristic had been observed in investment decisions at the Pakistan Stock Exchange by Parveen et al. (2020). In another study (Parveen et al., 2021) that took place during the COVID era, they showed that behavioral heuristics like anchored thinking and disposition effects had a negative effect on the trading decisions made by PSX investors when uncertainty is high. However, Chishti et al., (2025) built upon this study by recognizing the presence of halo bias and framing bias as new investment determinants at PSX with the help of SEM to create direct positive relationships. In the South Asian landscape, Maheshwari et al. (2025) were able to provide clear, convincing evidence from India showing that herding and fear-of-missing-out (FOMO) biases did not have a linear impact on investment decisions among Gen Z investors, but that the adoption of AI tools pushed the relationship to a third order.In the Indian context, Maheshwari et al. (2025) provided supportive evidence that herding and fear of missing out (FOMO) biases offered no significant linear effect on investment decisions among Gen Z investors; but rather, that the use of AI tools had a third-order effect. This was expanded by Saeed et al. (2025), who incorporated a mediator between the heuristic biases and investment decisions where they found that the use of AI further accentuates the heuristic biases for some while digital financial literacy helps to diminish them. This paper, by Malik et al. (2025), first proposes a ‘Bias Susceptibility Index (BSI)' derived through machine learning assisted regression at PSX; providing the first quantitative measurement of bias in emerging markets. Sharma, et al., (2024) have been the most relevant study for Nepal as they studied behavioural biases among 327 investors of NEPSE and concluded that the investors faced with the conflict between loss aversion, herding, experiential biases and financial risk propensity as a mediator were significantly influencing their investment decisions, which this study aims to replicate, extend and enrich with the integration of AI. Overconfidence was found to be the main determinant ($\beta = 0.421$) of investment decisions made at NEPSE by Adhikari et al. (2025) and pathak et al. (2024) used SEM to show that overconfidence bias and representative bias positively affected the behavior of investment decisions, and that the role of perceived market efficiency as an intermediate variable was identified between the role of overconfidence and representative bias.

2.3 AI and Machine Learning in Financial Markets

The use of AI, machine learning and NLP in finance has skyrocketed since 2020 and there is an abundance of empirical research on the predictive power, sentiment classification and algorithmic decision-making. Sathish et al. (2025) stated that the hybrid models, which are the combination of KNN and LR with sentiment analysis using NLP, have been continuously found to be better performing than any single-algorithm models for predicting the stock market. In their study, Agrawal et al. (2025) evaluated the sentiment analysis performance by BERT against the traditional price-based models in stock trend prediction and presented 98.92% accuracy which is significantly better in comparison. Chauhan et al. (2025) proposed a model called Sentipp which is based on CNN-GRU sentiment awareness and uses an LSTM time-series prediction model that provided better accuracy on FTSE, SSE, Nifty 50, and S&P 500 datasets. A critical review of these reveals a number of problems. Firstly, the majority of financial markets studies based on AI were for well-established and liquid markets like stock exchange, bond market, which can have a huge amount of digital sentiment data, while the application to less liquid markets like the emerging bond and stock markets, with low number of individuals using social media or vernacular language text is still in its infant stages. Second, the studies have established that the technical accuracy of AI has been demonstrated, but fewer have established a link between the behavioral economic aspects (how easy AI products are to use, how well it reduces investor biases, etc.) and the ability of predictive ML to reduce biases. Ullah et al., 2026, tackled this issue at part, showing that intelligent portfolios have more effective diversification but that traders with a blend of stocks and machine trading select from similar choices once they start to profit, suggesting that over-optimism is not eradicated by AI, but rather reshaped.

2.4 Market Efficiency Evidence for NEPSE

The literature on efficiency peculiar to Nepal is unanimous in rejecting the weak-form EMH, a finding that is key to the contextion of behavioral anomalies. By testing NEPSE data for the 11 sectors from 2013 to 2022 using the Kolmogorov-Smirnov, run tests and the Hurst exponent, Khanal et al. (2025) have found that each of the sectors is characterized by market inefficiency in the weak-form sense. In the sub-indices, significant serial correlation was observed in NEPSE indices with non-random behavior especially seen in microfinance, hydropower, banking, and development bank sub-indices respectively ranging between 0.821 and 0.995 (lag 1) in accordance with what Phulara et al. (2025) confirmed. The results of Joshi (2024) proved that the discounted past returns of NEPSE would statistically determine the trend of the future movements contrary to the hypothesis of the random walk of the EMH. Recently, Karki (2026) conducted three decades analysis using GARCH, Markov-switching models and found an efficiency regime in 2021–2025 spanning two distinct volatility regimes arising from the occurrence of structural shocks like earthquake (2015) and COVID (2020–21).

3. THEORETICAL FRAMEWORK

3.1 Prospect Theory

For this study, the underlying behavior lens is taken from Prospect theory created by Kahneman and Tversky (1979). Prospect Theory can deal with the investor's documented reactions to gains and losses in a way that does not involve multiplication by the appropriate loss aversion factor as in the case of expected utility theory; it predicts that investors would process an outcome as compared to a reference point rather than a base level of wealth; and it predicts the probability weighting of small probabilities and big probabilities, which is the tendency for investors to overweight small probabilities and underweight large ones. In today's NEPSE landscape, where nearly 68% of investors are first-time retail investors, and are entering into the market with NEPSE's post-2020 entry, the initial investment price of dematerialized shares is often the benchmark, and the asymmetric response to losses versus gains translates to actual investment and redemption behaviour.

3.2 Adaptive Market Hypothesis

In addition to the structural market-level complement, which is provided by Lo's (2004) Adaptive Market Hypothesis (AMH), there is the generational complement. The AMH takes a different view on market efficiency: Market efficiency is not a final equilibrium state, but a process as the investors change their heuristics and strategies in the process of selection, competition and environmental feedback. This model suggests information in primitive stages and economic efficiency in NEPSE will be low because of information, but in intermediate stages that economic efficiency will increase as information and regulatory changes becomes sophisticated, and in advanced stages due to the increasing financial literacy of the actors in the NEPSE. Most importantly, the AMH argues that AI tools, which help process information and could ultimately remove the trading edge for those who bring in information immediately, should gradually shrink anomaly time windows, but not drive them to extinction.

3.3 Human-Centered AI Design Theory

The Human-Centered Design principles advocated by Norman (1988) have been adapted for the realm of AI (Amershi et al. 2019) and the more recent literature on Industry 5.0, and are used here to reinforce the idea that design in AI should be done based on human limitations, not the rational processor's assumption. When applied to the space of behavioral finance AI tools, that means the tools that show investors sentiment dashboards, bias detection alerts, and robo-advisory nudges have to cater to individual investors' cognitive architectures (tendency to be framed, present biased, feeling information overload) and not just provide algorithmically optimal outputs.

3.4 Social Exchange Theory and Herding

Based on his Social Exchange Theory of Blau (1964), herding behaviour may occur when one active investor reasons the interactions with others can be traded for the reduced information costs and the perceived social legitimacy of conforming with the others; individuals who perceive the others have better information about value/information invest more in the collective, and others with less information follow to strengthen the mass turn. This exchange is accentuated in a very relational broker-investor environment like NEPSE, where social networks and informal information channels play a very central role for most investors, as the formal disclosure excepts are not of significant importance. An AI-empowered anomaly detection system can upset this balance by empowering individual investors to get access to objective sentiment information, normally acquired by sophisticated investors, at a lowered price.

3.5 Integrated Theoretical Model: The BADF

The research combines these four theories into a 'Behavioral Anomaly Detection Framework' (BADF) that proposes that cognitive biases, resulting from the Prospect Theory, create a systematic distortion in investment decision-making, whereas this systematic distortion aggregates into the market level biases which can be detected through tools which are consistent with AMH (as Random Walk Hypothesis suggests that such anomalies should be considered spurious), AI tools such as sentiment analysis and predictive analytics, built on human- centred rules, moderate the bias-decision relationship through accessible correction of information, and financial risk propensity, defined by Social Exchange dynamics, moderates the relationship between loss aversion, herd behaviour and investment outcomes. Refer to Figure 1 below (Conceptual Framework).

4. HYPOTHESIS DEVELOPMENT

Based in the integrated BADF and previous works, eight research-hypotheses are formulated: There is significant and positive relationship between overconfidence bias and suboptimal investment decision of NEPSE investor. This theory is based on Prospect or Shift theory (Kahneman & Tversky, 1979) and supported by Adhikari et al. (2025) whose study revealed strongest predictive beta ($\beta = 0.421$) for overconfidence in NEPSE and Ullah et al. (2026) who concluded that overconfident hybrid investors do worse than algorithm-only portfolios at PSX. The result shows Herding behaviour has a significant positive impact on suboptimal investment decision. This hypothesis is supported by the findings of the social information cascade literature (Bikhchandani et al., 1992) and other evidence specific to NEPSE gained from Chand's (2024) study, where she found herding to be the strongest behavioural predictor ($\beta = 0.463$). Herder dominance has also been confirmed by the study carried out by Karmacharya et. al., (2022). There is significant and positive evidence of the extent to which loss aversion affects suboptimal investment decisions. Sharma et al. (2024) have identified high level of loss aversion effect through financial risk propensity at NEPSE. It played a role during the COVID shock at PSX as confirmed by Parveen et al. (2021). H4: Anchoring bias has significant positive impact with high degree on sub-optimal investments decisions. Market efficiency was found to play a mediating role between the anchoring and the decision in the case of NEPSE (Pathak et al. 2024), therefore the direct effect of the anchoring needs to be tested statistically. We confirm the anchoring heuristics at PSX as stated by Parveen et al. (2021). H5: Sub optimal investment decision is significantly and positively impacted by Regret aversion bias. However, regret aversion was found to have a direct effect on investment decision making among Indian Gen Z investors by Maheshwari et al. (2025) and regret is recognized as a unique and significant construct in behavioral research. The Hypotheses are as follows: H1: Financial risk perception has a direct effect on suboptimal investment decision; H2:

Financial risk propensity significantly mediates the financial risk perception – suboptimal investment decision relationship; and H3: Loss aversion significantly influences financial risk proneness. Sharma et al. (2024) found mediation in NEPSE, this hypothesis tested the robustness of this finding by using a larger sample of NEPSE using AI-enhanced data. H7: The link between a bias in decision making and herding behavior is significantly affected by the extent of the use of AI in investment decisions and this effect is negative, resulting in a reduced bias-decision link. This builds on the moderation findings in India by Maheshwari et al. (2025) and extends the possibility of reshaping behavioural biases caused by AI tools made by Ullah et al. (2026) to Nepal. There is statistical significance in the predictive accuracy (>85%) of sentiment classification using AI driven sentiment analysis models from NEPS investor sentiment category. According to Agrawal et al. (2025) and Sathish et al. (2025), BERT and hybrid ML systems always exhibit better accuracy for sentiment classification in the financial context.

5. RESEARCH METHODOLOGY

5.1 Research Philosophy and Design

Given this post-positivist approach to philosophy, this study takes the following steps: first it accepts that the objective market data and real facts of prices, volume and distribution of anomalies can be obtained to a more or less approximate degree of reliability; second, the study recognises that there is intrinsic variability in investor psychology, and that this must be treated both quantitatively and qualitatively. The problems are solved using sequential explanatory mixed-method design (Creswell & Plano Clark, 2018) namely quantitative data collection and analysis is done first then followed by qualitative data collection and explanation, the qualitative data collection is expected to give description for further analysis as the cause of the statistical findings. It is especially suitable for behavioural finance studies in an emerging market such as Nepal where investor decision making may be fully embedded in the social and mores-localised context in which the investors operate, thereby extending beyond what can be captured by the nature of survey data.

5.2 Population, Sampling, and Sample Size

The target population includes all active individual investors who are registered with the brokers of NEPSE, and the CDS (Central Depository System) of Nepal by the end of the year 2024, in which there are around 5.2 million Demat account holders (Securities Board of Nepal, 2024). Stratified random sampling method was used with strata categories as: individual investors who are retail (80%), institutional (12%) and broker dealer (8%); as Bagmati Province (42%), Gandaki (18%), Madhesh (15%), Lumbini (12%) and others (13%) of various provinces; and as experience level of investors (< 2 years: 35%, 2 years to 5 years: 40% and above 5 years: 25%). The minimum sample size of PLS-SEM (with 8 predictors) is determined using G*Power 3.1 with power = 0.80, effect size $f^2 = 0.15$ and the significance level $\alpha = 0.05$, resulting in a minimum n = 142. A total of n = 547 was targeted for the study due to the associated power of = 0.99 and the ability to run the multi-group analysis. After removing questionnaires that were not completed and straight-line responses, the final data sample for analysis consisted of n = 547 questionnaires (a response rate of 84.2%) and 22 qualitative interviews.

5.3 Measurement Instruments

Each behavioral bias constructs was measured with an adapted, multi-scale instrument that has been used in previous studies in the field of behavioral finance. The following five items adapted from Barber & Odean (2001), Adhikari et al. (2025) were used to measure the overconfidence bias. From Bikhchandani et al. (1992) & Chand (2024), 4 items were used to measure herd behavior. The 4 items from the loss aversion scale validated by Sharma et al. (2024) were used to measure loss aversion. Anchoring bias was not measured using any items but rather 4 items from Anandan et al. (2016). For regret aversion, 3 items as taken from Dushmanza and Monfort (2007) were used. 5 items – taken from Maheshwari et al. (2025) – were used for AI adoption, 4 items – taken from Masedi and Tshwane (2008) – were used for financial risk propensity, and 5 items – taken from Maheshwari et al. (2025) – were used for investment decision quality. The five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was used for all items.

5.4 Data Collection Procedures

The data collected in this study is quantitative collected through a structured questionnaire on the online-offline hybrid approach through NEPSE registered brokerage firms in Kathmandu, Pokhara, Biratnagar, Butwal and Birgunj from January to April 2025. The questionnaire was pretested on 45 investors and the items where the item-total correlation was less than 0.40 were changed. Secondary data comprised the daily closing NEPSE composite index value and closing value of the sub-indices (banking, hydropower, microfinance, insurance, manufacturing and development bank sub-index) value for January 2019 to February 2025 from the official database of NEPSE (www.nepalstock.com). A collection of investor's social media posts (184,200), forum conversations (ShareSansar and ShareSansar-MeroLagani) and financial news articles (Karobar Daily and Arthik Abhiyan) were created covering the time period of 2021-2025 for AI sentiment analysis. The text was processed before classification, including transliteration to Nepali language using IndicNLP libraries, tokenization and sentiment labeling using a combination of VADER and BERT libraries.Preprocessing was done to the texts, which included transliterating Nepali text and using the IndicNLP libraries, tokenization, and using a hybrid VADER-BERT pipeline for sentiment labeling.

5.5 Analytical Methods and Software

Five software environments, all of which are statistical, were used for statistical analysis. Wilcoxon t-test, ANOVA and reliability analysis (Cronbach alpha) were used in SPSS 28 for descriptive statistics. PLS-SEM was used by smartPLS 4.0, the assessment of the measurement models by AVE, CR, HTMT and Fornell-Larcker criteria, and the FT based on bootstrapping with 5,000 iterations. Confirmatory factor analysis and additional estimation of SEM were conducted using R packages lavaan, semPlot, and mediation, version: 4.3.1. Sentiment analysis, machine learning pipeline construction and visualization were done using Python 3.11 alongside various libraries including skikit-learn, transformers/BERT, NLTK, pandas and matplotlib and seaborn. The time-series analysis was provided by Stata 17 techniques such as GARCH/ARCH, the various Markov-switching efficiency tests, and the robustness checks for endogeneity using IV regression.

5.6 Ethical Considerations

The study received an ethical clearance from IRC and Informed written consent was obtained and participation was anonymous and voluntary. Access of the organizations has been negotiated on the basis of formal agreements with NEPSE registered association of brokerages. All data were recorded in secured repositories according to the guidelines of Individual Privacy Act, 2018, Nepal and any information that could be used to identify the individual was not stored anywhere beyond the scope of the study. Member-checking and reflexive bracketing protocol were used in the qualitative phase.

6.1 Demographic Profile of Respondents

Table 1 presents the demographic characteristics of the final analytical sample (n = 547).

Variable	Category / Range	Frequency (%)
Gender	Male	374 (68.4%)
	Female	161 (29.4%)
	Other / Prefer not to say	12 (2.2%)
Age	18–25 years	138 (25.2%)
	26–35 years	201 (36.7%)
	36–45 years	129 (23.6%)
	46–55 years	57 (10.4%)
	56+ years	22 (4.0%)
Education	Secondary (SLC/SEE)	89 (16.3%)
	Intermediate (+2)	112 (20.5%)
	Bachelor's Degree	234 (42.8%)
	Master's / MPhil	98 (17.9%)
	PhD / Doctoral	14 (2.6%)
Occupation	Employed (private)	198 (36.2%)
	Employed (government)	121 (22.1%)
	Self-employed / Business	143 (26.1%)
	Student	62 (11.3%)
	Retired / Other	23 (4.2%)
Investing Experience	Less than 2 years	193 (35.3%)
	2–5 years	214 (39.1%)
	More than 5 years	140 (25.6%)
AI Tool Usage	Regularly	162 (29.6%)
	Occasionally	231 (42.2%)
	Never	154 (28.2%)

Note: n = 547. Percentages may not sum to 100 due to rounding.

6.2 Descriptive Statistics and Reliability

Table 2 presents descriptive statistics and reliability coefficients for all constructs.

Construct	Items	Mean	SD	Skew.	Cronbach α	CR
Overconfidence Bias (OB)	5	3.72	0.74	-0.41	0.881	0.912
Herding Behavior (HB)	4	3.58	0.81	-0.29	0.864	0.903
Loss Aversion (LA)	4	3.41	0.79	0.18	0.852	0.894
Anchoring Bias (AB)	4	3.34	0.82	0.22	0.847	0.889
Regret Aversion (RA)	3	3.29	0.77	0.31	0.831	0.878
AI Adoption (AI)	5	3.12	0.88	0.09	0.869	0.908
Financial Risk Propensity (FRP)	4	3.23	0.76	0.14	0.841	0.884
Investment Decision (ID)	5	3.45	0.80	-0.19	0.876	0.909

Note: All Cronbach alpha values exceed the 0.80 threshold; CR values exceed 0.87, confirming strong construct reliability.

6.3 Measurement Model: Validity Assessment

Table 3 presents AVE, and HTMT ratios from the SmartPLS 4.0 confirmatory factor analysis.

Construct	AVE	HTMT Ratios (all < 0.85 threshold)
OB	0.631	OB–HB: 0.621; OB–LA: 0.578; OB–AB: 0.543; OB–RA: 0.512
HB	0.614	HB–LA: 0.589; HB–AB: 0.567; HB–RA: 0.534; HB–ID: 0.701
LA	0.604	LA–AB: 0.598; LA–RA: 0.571; LA–FRP: 0.623; LA–ID: 0.672
AB	0.596	AB–RA: 0.548; AB–ID: 0.618; AB–AI: 0.421
RA	0.591	RA–ID: 0.601; RA–FRP: 0.541; RA–AI: 0.389
AI	0.618	AI–ID: 0.598; AI–FRP: 0.512; AI–HB: 0.421
FRP	0.602	FRP–ID: 0.641; FRP–LA: 0.623
ID	0.625	All ratios below threshold — discriminant validity confirmed

Note: AVE values exceed 0.50 (Fornell-Larcker criterion satisfied). HTMT < 0.85 confirms discriminant validity. CFA loadings ranged 0.721–0.891 (all significant at $p < 0.001$).

6.4 PLS-SEM Results: Direct Effects and Hypothesis Testing

Table 4 presents the PLS-SEM structural path results and hypothesis outcomes.

H	Path	Beta (β)	t-Value	p-Value	R^2	Decision
H1	OB → ID	0.431	7.821	< 0.001		Supported
H2	HB → ID	0.389	6.912	< 0.001		Supported
H3	LA → ID	0.312	5.634	< 0.001		Supported
H4	AB → ID	0.278	4.891	< 0.01		Supported
H5	RA → ID	0.241	4.213	< 0.01		Supported

H	Path	Beta (β)	t-Value	p-Value	R²	Decision
—	Model R² (ID)	—	—	—	0.671	Adequate
—	Q² (predictive relevance)	—	—	—	0.489	Adequate
—	Effect sizes (f²): OB=0.28; HB=0.24; LA=0.19; AB=0.16; RA=0.14					

6.5 Mediation Analysis (H6): Financial Risk Propensity

Partial mediation was confirmed using a mediation analysis with -5,000 bootstrapped iterations. The indirect pathway of Loss Aversion on Investment Decisions, through the Financial Risk Propensity, was: β_indirect = 0.118 [0.071, 0.183] $p < 0.001$. The partial mediation is indicated by the direct model of LA: the direct effect of LA on ID remained significant with FRP in (β_direct = 0.194, $p < 0.001$). H6 is supported.

6.6 Moderation Analysis (H7): AI Adoption

The mean-centered values of each term were used for calculation of Interaction term (HB × AI Adoption). Both the interaction term and economic significance were statistically significant with a negative sign (β_interaction = -0.187, $t = 3.421$, and $p < 0.001$), suggesting that the positive relationship between herding and investment decision was reduced as AI was increased. HB-ID experiences a β value of 0.389 at 1 std dev above the mean in terms of AI adoption; this falls to β = 0.202. The H7 approach is supported as Maheshwari et al. (2025) said.

6.7 AI-Driven Sentiment Analysis Results (H8)

The trained BERT based sentiment classifier on 147360 labeled dataset has 91.7% accuracy, precision of 90.4% and recall of 91.2% with F1 of 0.908 in test phase. After many experiments, it was found that the hybrid BERT + LSTM ensemble model could beat the original BERT by 93.2%, which is in agreement with the results of Agrawal et al. (2025). Three major events of pessimism prior to the index movements (Q2 2021 NEPSE crash, Q3 2022 liquidity crisis and Q1 2024 interest rate spike), and two peaks of positivity that came before or appeared concurrently with the index movements (Q3 2023, Q2 2024) have been measured using the sentiment polarity time-series from 2021 to 2025, along with detected movement patterns and/or macro-economic and financial events that further reinforce said predictive behavioral relevance. H8 is supported.

6.8 Market Efficiency and Anomaly Testing

Based on the Hurst exponent, run tests and autocorrelation diagnostics applied to NEPSE composite and sub-index returns (2019-2025), the Hurst exponents were also found to be in line with Khanal et al (2025) as persistent non-random behavior emerged with a Hurst exponent of 0.731 ($H > 0.5$ shows positive autocorrelation / trending). The GARCH(1,1) estimation found that there is high volatility persistence ($\alpha + \beta = 0.889$); the Markov-switching models found that there are two regimes of volatility: low (duration ~17 days) and high (duration ~11 days), very close to the volatility identified in identified sentiment crisis episodes. The January effect and the pre-dividend announcement anomalies were significant (at 5% level) in the banking sub-index.

7. DISCUSSION

7.1 Behavioral Bias Determinants of Investment Decisions

The PLS-SEM findings reveals an interdependent relationship that loss aversion is the second most dominant behavioural bias factor affecting NEPSE, followed by herding, then overconfidence before anchoring, and regret aversion. The overall model accounts for 67.1% of the variances in the performance of investment decision quality, which is much higher than the explanatory power of most of the NEPSE specific lapsed models. The single-bias model proposed by Adhikari et al. (2025) accounted for only 59.1% of the variance with overconfidence alone, and but the multivariate integration revealed that there were significant unique contributions for each of the bias constructs. Insider trading may have been easier prior to the economic crisis: Perhaps psychologically, the overconfidence factor was greater than in latter years, underpinned by the fact that investors are psychologically likely to be systematically overconfident about their predictive ability, and feel that they possess more knowledge. That is even more true in Nepal, where youthful investors with a healthy appetite for technology are trading in a bull market with minimal adversarial background on trading. Additionally, due to the NEPSE rally in 2020-2021, there were such initial conditions for the market entrance of the stocks in the rally which left them with an overconfident belief that can be explained with the help of the concept of cognitive learning theory (Gervais & Odean, 2001). This finding is in line with PSX evidence by Ullah et al. (2026) that overconfidence is not removed from the game by using AI, but instead appears in different forms: selectively ignoring the machine's recommendations after initial profitable trades. The herding coefficient for this study was $\beta = 0.389$ and meets with Chand's (2024) result of herding as top single predictor for investment activities at NEPSE, which was reported as $\beta = 0.463$ and Karmacharya et al.'s (2022) result of market information factors as top driver of investment activities at NEPSE, which is reported as $\beta = 0.616$. Nepal's herding dynamic is uniquely social in several aspects: market participation has no in-person coverage of skilled analysts, there are no broker tip networks (mostly known by the local term 'saathi' trading) and investment advice proliferates via Facebook groups and ShareSansar forums with ease, which closely resembles Bikhchandani et al.'s (1992) theoretical cascade model. By introducing objective AI sentiment data, the result of the AI moderation finding (H7, $\beta\_interaction = -0.187$) indicates that it partially breaks these cascades, which aligns with the findings of Saeed et al., 2025, that cascades of heuristic bias are partially mediated with digital financial literacy.

7.2 Mediation by Financial Risk Propensity

The partial mediation of loss aversion's effect found in this study (indirect $\beta = 0.118$, CI [0.071, 0.183]) replicates and extends Sharma et al.'s (2024) mediation result with 327 to 547 investors which significantly bolsters the generalizability of such mediation pattern. A cognitive intermediary between loss aversion and decision quality is the variation of financial risk propensity that describes the mindset of the trader as reflected in return expectations, the time horizon and diversification options. The highly loss averse investors have cautious risk behaviour characteristics and tend towards not diversifying their portfolios and developing holding biases, which may eventually reduce individual risk adjusted investment outcomes. The mediation pathway has significance for the pragmatic implications. The interventions that could be directly applied to financial risk propensity (besides abstract educational campaign on loss aversion) might hold great promise of doing so in a direct way (mediating mechanism), because the application is based on personalized risk profiling tools integrated into NEPSE trading platforms. One type of potentially transformative intervention that can work with this mechanism is the AI driven robo-advisor, which adapts the recommendations of the portfolio to meet the specific risk profile of the individual in real time, with the specific calculations believed to be accurate.

7.3 AI Adoption and Behavioral Anomaly Moderation

This moderate finding — a negative statistical relationship between the herding-decision relationship and the adoption of AI ($p < 0.001$, with $\beta = -0.187$) — is another significant addition to the on-going literature on AI and behavioral finance. Using an AI-driven digital advisory service, Maheshwari et al. (2025) also discovered FOMO moment and herding among Gen Z investors in India. But in the present study, the lower rate of regular use of AI tools in NEPSE (29.6% of respondents are using AI regularly compared to India's higher AI use in fintech) indicates that the benefit of bias attenuation is maximized by simply using AI to a certain extent rather than more. When comparing with the celebrity-focused accuracy of sentiment classification tools using AI, the sentiment analysis results obtained by BERT here (test accuracy 91.7%; ensemble accuracy 93.2%) place the NEPSE-friendly sentiment classification tools at the leading edge of accuracy on tests of emerging market sentiment classification, on par with Agrawal et al.'s (2025) test accuracy of 98.92% for the Dow Jones data. This figure reflects the inherent differences between the size of the respective corpora as well as quality differences between the sources of mature markets and sources of frontier markets, but also indicates significant scope for improvement as the size and quality of the data sets for Nepali increase.

7.4 Market Efficiency and the Adaptive Market Hypothesis

By observing the PPE, NEPSE is a market that won't clear the lower bound of H, which is one of the definitions of non-market efficiency. Markov switching GARCH volatility persistence ($\alpha + \beta = 0.889$) also reinforce that NEPSE is not market where a lot of behavioral anomalies cannot easily be arbitraged away. The structural properties of NEPSE provide the foundation over which behavioral biases exert decision-impairing effects. It aligns well with the results of Karki (2026) based on AMH that NEPSE is inefficient but is shifting towards better efficiency during the time frame considered below.This is in line with the work of Karki (2026) where he found that emerging but incomplete efficiency exists in NEPSE which directly contradicts to weak form EMH for the time frame considered in the study. A correlation analysis of the returns of the banking sector benchmark with January and pre-dividend anomalies, includes findings that investors holding informed views on these anomalies and algorithms that can spot them, may find some interesting reasons to do so in this sector of the economy.A sector based analysis of the returns in the banking sub-standard indicates the presence of January and pre-dividend anomalies suggesting some reasons to hold informed views on such anomalies as well as reasons to develop algorithms that can identify them – just the kind of anomaly detection this study's BADF architecture can support.

7.5 Unexpected Findings and Theoretical Implications

Two of the results are of particular interest. Statistically ($\beta = 0.241$, $p < 0.01$), the least mentioned of the five biases in NEPSE literature emerged as regret aversion. The qualitative interviews conducted here (thematic analysis of 22 institutional informants) showed the different-preston failure regret observed in Nepal – opportunity regret, i.e. fearing the missed opportunities to benefit from market hikes, as opposed to the familiar Western experience of regret after losing money – with the social salience of investment outcomes in tightly bound broker networks. This discovery constitutes an extension of Prospect Theory suggesting cultural reference points of regret in financial situations that assume a collectivist culture. Second, herding didn't significantly moderate as a result of adopting AI, but neither did it reduce herds' overconfidence, as counterintuitive as that may seem.As far as that goes, herding didn't significantly moderate as a result of adopting AI, though that can feel counterintuitive, particularly people who are accusing others of overconfidence in using it. Why AI fails to modify overconfidence could also point to how incompatible overconfidence is with the information-correction mechanisms: the incentives a humantype AI is going to have to change an overconfident decision maker's mind will be different from the incentives a human would have to change it, and therefore the designers of the system will need to intentionally make the AI user experience uncomfortable and friction-filled, again in accordance with the general principles of human-centered AI design (Amershi et al., 2019).

8. CONCLUSION

The aim of this study was to develop and test an AI-Driven Behavioral Anomaly Detection Framework (BADF) for the Nepal Stock Exchange, combining all the concepts from three theories namely prospect theory, Adaptive Market Hypothesis, and design of Human-centric AI. Five behavioral biases (overconfidence, herding, loss aversion, anchoring, and regret aversion) were validated as significant factors individually association with the investment decision quality and their combination explained 67.1% of the variance in investment decision quality in the sample of 547 NEPSE investors. Financial risk propensity partially moderates the relationship between loss aversion and investors while AI adoption significantly reduces such a relationship between herding and decision, illustrating the potential of AI tools to moderate emerging market investors' decisions. Indeed, NEPSE is showing continued signs of market inefficiency as per the Adaptive Market Hypothesis (AMH), with a Hurst exponent of 0.731 and a GARCH persistence of 0.889 leaving structural conditions, where it is possible for behavioral biases to have a corrosive effect. The performance of AI-powered BERT sentiment analysis was validated by its ability to classify investor sentiment, with an accuracy of 91.7 – 93.2% in the corpora of Nepali financial media, which demonstrated the potential of real-time investor sentiment monitoring system within the Nepalese stock exchange's digital infrastructure. Regulating emerging market technologies and app creators can use the BADF as a replicable, theoretically cohesive, and practically viable blueprint to understand how to employ AI to promote investor gratification and sound market dynamics. The big idea in the framework is the ability to link measurement of behavioural bias, emergence of sentiment from artificial intelligence and the development of a causal model of adaptive market efficiency in a unified structure, overcoming fundamental defects in frontier emerging markets behavioural finance research.

9. RESEARCH IMPLICATIONS

9.1 Theoretical Implications

This study contributes to the study of behavioral finance in the following significant ways. First, it shows that overconfidence and herding tendencies are mediated differently since they are moderated differently by adopting AI, which enhances the theoretical knowledge about the interaction of AI with cognitive bias architecture. Second, the 'opportunity regret' form of regret aversion is found only in the West and has been identified in the collectivistic context of investors in Nepal and poses challenges for the universal application of Western formulations of Prospect Theory. Third, the AMH with the introduction of the AI-powered anomaly detection mechanism is the first formal connection between evolutionary market efficiency theory and computational behavioral analytics in a frontier emerging market environment.

9.2 Practical Implications for Investors and Brokers

Finally, the study's bias hierarchy pinpoints overconfidence and herding as investor bias to be targeted through investor behavior self-regulation for the individual investor. The findings from this study can be directly applied to practical debiasing strategies, such as structured pre-trade checklists, mandatory waiting periods on large transactions and automated lists of the "contrarian sentiment." For brokerage firms, adding investor sentiment dashboards and bias susceptibility indices based on BERT into trading management systems are innovative and good for the welfare because they are cost-effective.

9.3 Policy Implications for SEBON and NEPSE

A regulatory mechanism must be put in place by the Securities Board of Nepal (SEBON) that encompasses principles of behavioral finance. Specifically, SEBON should implement behavioural based risk disclosure in the case of broker-client relationships, AI literacy initiatives for retail investors as part of its Investor Awareness Programs and possibly mandate nudges to retail investors in cases of transactions exceeding some threshold while using a robo-advisor service. We believe that the identified January effect and dividend announcement anomalies in the banking sub-index indicate that a behavioral behavior anomaly pattern surveillance mechanism ought to be brought into the surveillance framework in addition to the traditional manipulation detection. Again, the AMH consistent finding of time varying efficiency supports the current reforms in the digital infrastructure put in place by SEBON as efficiency enhancing interventions.

9.4 Societal and Educational Implications

With an estimated 72% of the population having a smartphone in Nepal and the rapid growth in digital Demat account, a paradigm shift is taking place in the financial sector, which is becoming increasingly accessible to people.The financial sector is experiencing a remarkable democratization in Nepal with the penetration of Smartphones (estimated at 72% in 2024) and the growth rate in the number of digital Demat accounts. With 62% in the age group 18–35 and known as the most susceptible to herd behavior, the results indicate a pressing need for implementation of the modules of behavioural finance in the university Business and Economics curriculum as well as digitised financial education platforms; and AI-driven investment education. The regret aversion finding is cultural in nature and this implies that financial education programs need to go beyond tackling individual cognitive biases and have to look at the social facet of investment communities in Nepal's broker network chain.

10. LIMITATIONS

These conclusions must be qualified as representing the following five main limitations. First, even with the stratification design, there might be selection bias in brokerages due to their convenience and accessibility to those interested in investing electronically and more financially. Higher financially literate investors might be overrepresented as compared to the total portfolio of NEPSE investors, which could minimise a bias in the financial literacy of less informed investors. Secondly, the cross-sectional quantitative component records one time instant of investors' psychology. The study period (January-April 2025) captured a moderately stable NEPSE environment which may not capture all the dimensions of the intensification of behavioral bias in the wake of heightened market stress episodes, especially the loss aversion and herding. Third, common method bias (CMB) also arises as an issue in the process of self-report data collection in surveys. Although Harman's single factor test (largest accounted for variance = 26.8%) and the split between bias and outcome in the questionnaire reduce this risk some bias cannot eliminated by CMB. Thirdly, the large data set of the NLP sentiment corpus (184,200 texts), is also biased towards Romanised Nepali and English content coming from urban platforms (ShareSansar, Mero Lagani). The AI analysis, predominantly based on broker telephone calls, does not contain rural investor sentiment as such, which could lead to a structural bias of urban sentiment. Fifth, the results of the AI Moderation Task in the study are only relevant to reported AI tool usage and not to random exposure to AI interventions. While it is possible to control for endogeneity concerns in an observational design — due to time-invariant differences in investor susceptibility to being part of a herd, after all — this effect is more completely dealt with in Stata (IV) regression.

11. FUTURE RESEARCH DIRECTIONS

Based on these findings, the results can yield 10 substantive lines of research for the future. In addition, cross-sectional nature of the current market cycle study may be overcome by adding time dimension that allows causal inference and learning dynamics to be explored using the data from a longitudinal panel. Second, RDTs in which NEPSE investors are randomized to receive either instructions with AI or without showed causal evidence on the effectiveness of AI in debiasing. Third, cross-national comparative studies would be conducted between the BADF and structurally similar frontier markets (such as DSE in Bangladesh, CSE in Sri Lanka, securities exchange in Myanmar) would bring to the fore the need for and scope of potential cross-contextual transferability of the BADF and the existence of culture-specific bias modifications.

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