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Chapter 4: Behavioural Biases and Portfolio Decisions among Individual Equity Investors

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Abstract— Individual equity investors increasingly make portfolio decisions in information-rich environments shaped by digital trading platforms, social-media signals, real-time market alerts, and automated recommendation systems. Despite wider access to financial information, investment behaviour frequently departs from the assumptions of fully rational portfolio choice because psychological biases affect risk interpretation, stock selection, diversification, and trading frequency. This study proposes a behavioural-computational framework for examining how overconfidence, herding, loss aversion, anchoring, representativeness, and mental accounting jointly influence portfolio decisions among individual equity investors. The central research gap is that much of the existing literature evaluates behavioural biases independently through conventional regression or structural-equation models, whereas comparatively limited attention has been given to nonlinear combinations of biases that distinguish disciplined from behaviourally distorted portfolio choices. To address this gap, the proposed study conceptualises portfolio decision quality as a multidimensional outcome incorporating diversification adequacy, turnover discipline, concentration risk, risk-return alignment, and resistance to short-term market imitation.

Keywords— Behavioural Finance, Individual Equity Investors, Portfolio Decisions, Overconfidence Bias, Herding Behaviour, Explainable Machine Learning

Introduction

The expansion of digital brokerage platforms has substantially changed the environment in which individual investors participate in equity markets. Investors can now obtain quotations, company announcements, technical indicators, analyst opinions, financial commentary, social-media discussions, and portfolio analytics almost instantaneously. Low-friction trading interfaces have also shortened the distance between receiving information and executing a transaction. Although this transformation has improved market accessibility, it has not necessarily produced consistently rational investment behaviour. Instead, investors must process larger quantities of heterogeneous information under conditions of uncertainty, time pressure, incomplete knowledge, and emotional exposure to gains and losses.

Classical portfolio theory generally treats investment choice as a process in which individuals evaluate expected return and risk and select combinations of securities that maximise utility subject to their preferences and constraints. Behavioural finance challenges the assumption that such evaluations are always internally consistent. Investors commonly rely on cognitive

shortcuts, emotional reactions, previous reference points, recent experiences, and observations of other market participants. Consequently, a portfolio may reflect psychological predispositions as strongly as objective assessments of expected risk and return.

One particularly important behavioural tendency is **overconfidence**. An investor who overestimates the precision of personal information or forecasting ability may trade excessively, underestimate uncertainty, or maintain concentrated positions because the perceived superiority of the investment thesis discourages diversification. The continuing relevance of overconfidence has been documented extensively in behavioural-finance research. A recent systematic mapping of the literature identifies overconfidence as one of the most persistent biases affecting investment decisions and trading behaviour.

A second influential tendency is **herding**, whereby investors imitate the observed or perceived behaviour of other market participants rather than relying exclusively on independent analysis. Digital investing can intensify this mechanism because popularity indicators, discussion forums, investment influencers, rapidly circulating market narratives, and visible price momentum create continuous social signals. Herding does not require literal copying of another person's transaction. It may occur when investors interpret rising attention itself as evidence that a security is attractive.

Loss aversion introduces another distortion. Prospect theory establishes that decision makers evaluate outcomes relative to reference points and generally treat losses differently from gains of comparable magnitude. This asymmetry provides a theoretical basis for behaviours such as retaining losing securities for excessive periods, realising profitable positions prematurely, or avoiding necessary portfolio rebalancing after adverse price movements. The foundational contribution of Kahneman and Tversky remains central to understanding such reference-dependent behaviour.

Portfolio decisions may additionally be influenced by **anchoring**, **representativeness**, and **mental accounting**. Anchoring occurs when investors attach disproportionate importance to an initial value, such as a purchase price, previous market high, analyst target, or historical valuation. Representativeness arises when recent performance or salient characteristics are treated as reliable indicators of future performance even when available evidence is insufficient. Mental accounting occurs when investors divide wealth into psychologically distinct categories rather than evaluating total portfolio exposure comprehensively. These biases can influence not only whether a security is purchased or sold but also how capital is allocated across securities.

Empirical studies have confirmed that behavioural biases are multidimensional rather than isolated phenomena. Research on individual equity investors has identified availability, representativeness, overconfidence, herding, anchoring, mental accounting, regret aversion, gamblers' fallacy, and loss aversion as distinct components affecting investor decision processes. Jain et al. developed and empirically evaluated a multidimensional behavioural-bias scale specifically for equity investors, demonstrating that several cognitive and emotional mechanisms can operate simultaneously.



Fig. 1: Behavioural Biases

Source: <https://www.precize.in/blogs/what-are-behavioural-biases->

This multidimensionality raises an important methodological problem. Much of behavioural-investment research estimates the independent or mediated effect of a limited number of biases using linear regression, fuzzy analytic hierarchy processes, or structural-equation modelling. Such methods are valuable for hypothesis testing but generally prespecify functional relationships. They may therefore underrepresent nonlinear interactions. For example, moderate overconfidence alone may not produce severe portfolio concentration, but overconfidence combined with representativeness and recent positive returns may sharply increase the probability of concentrated momentum-driven investment. Likewise, loss aversion combined with anchoring may be more influential in determining the retention of underperforming shares than either construct considered separately.

Recent empirical research supports the importance of examining such connected behavioural processes. Jain et al. investigated heuristic biases among 432 individual equity investors trading through the National Stock Exchange and found that risk perception mediated the relationship between several heuristics and investment decision-making. Their findings demonstrate that biases can operate through intermediate cognitive mechanisms rather than exclusively through direct effects. Similarly, Jain et al. reported that financial literacy influenced investment decisions while herding and

overconfidence acted as serial mediators, reinforcing the argument that investor behaviour emerges from linked rather than isolated psychological processes.

1.1 Research Gap

The specific gap addressed by the present study concerns the distinction between **bias measurement** and **portfolio-decision prediction**. Previous studies have made substantial progress in establishing whether individual behavioural biases significantly affect investment decision-making. Fuzzy-AHP research, for example, has ranked herding, loss aversion, and overconfidence among influential biases affecting equity investors. Other research has examined mediating mechanisms involving financial literacy and risk perception.

However, three unresolved issues remain.

First, investment decisions are frequently measured as broad self-reported constructs rather than as distinct portfolio-choice outcomes. An investor may simultaneously exhibit strong stock-selection confidence, excessive turnover, inadequate diversification, and reluctance to sell losing positions. Combining these behaviours into a single general investment-decision score may conceal economically meaningful distinctions.

Second, conventional linear models are not designed primarily to identify complex thresholds and interaction structures among several behavioural biases. The effect of herding, for instance, may depend on investment experience, market volatility, portfolio concentration, or overconfidence.

Third, relatively little behavioural-finance research integrates interpretable machine learning with behavioural survey data to classify portfolio decision quality while retaining an explanation of why the model assigns an investor to a particular behavioural-risk category.

The proposed manuscript therefore treats behavioural biases as a **joint predictive profile** rather than only as separate explanatory variables. It seeks to determine which combinations of cognitive and emotional biases are associated with poorly diversified, excessively active, or risk-misaligned portfolios and whether explainable machine learning can detect these relationships more effectively than a conventional linear benchmark.

1.2 Research Objectives

The principal objective is to develop an interpretable behavioural-analytics framework for predicting portfolio decision quality among individual equity investors. More specifically, the study will examine the individual and combined influence of overconfidence, herding, loss aversion, anchoring, representativeness, and mental accounting; construct a portfolio-decision quality index incorporating diversification, concentration, turnover, rebalancing discipline, and risk-return alignment; compare conventional statistical classification with nonlinear machine-learning models; and use explainability techniques to identify the behavioural factors and interaction patterns most strongly associated with suboptimal portfolio decisions.

Literature Review

2.1 Behavioural Finance and Portfolio Choice

Behavioural finance emerged from the recognition that actual financial decisions frequently violate the behavioural assumptions embedded in fully rational economic models. Investors do not always update beliefs according to formal probabilistic rules, treat equivalent outcomes identically, or maintain stable preferences across changing contexts. Portfolio decisions are therefore influenced by both economic information and the manner in which that information is cognitively processed.

Prospect theory provides one of the most important theoretical foundations for this argument. It proposes reference-dependent evaluation of gains and losses and asymmetric sensitivity to negative outcomes. Within investment settings, this mechanism can influence the timing of sales, willingness to rebalance, perceived attractiveness of risky securities, and reactions to unrealised losses.

Behavioural-finance research subsequently expanded beyond loss aversion to encompass a wide range of heuristics and biases. Jain, Walia, and Gupta examined multiple behavioural dimensions influencing individual equity investors and found herding, loss aversion, and overconfidence particularly influential in their fuzzy-AHP framework. Their work demonstrates that portfolio decisions cannot be adequately explained through a single psychological tendency.

2.2 Overconfidence and Active Portfolio Management

Overconfidence refers broadly to excessive confidence in one's knowledge, predictions, information-processing capacity, or investment skill. Within equity markets, the bias has several potential portfolio consequences.

An overconfident investor may assign excessive precision to personal forecasts. As a result, estimated differences between expected returns across stocks appear larger or more reliable than they objectively are. This encourages active stock selection and can reduce the perceived value of diversification. The same mechanism can increase trading because investors repeatedly act on signals they consider informative.

Overconfidence may also alter learning from historical outcomes. Profitable trades can be attributed disproportionately to skill, while losses may be attributed to unusual external conditions. Such asymmetric attribution maintains confidence even when realised evidence should encourage belief revision. The systematic mapping undertaken by Kumar and Prince confirms that overconfidence remains a major theme in contemporary behavioural-investment scholarship and is closely connected with investment decisions and trading activity.

An important implication for the present study is that overconfidence should not be treated solely as a direct determinant of investment choice. Its influence may become materially stronger when combined with recent-return extrapolation, representativeness, or low perceived risk. Machine-learning models provide one avenue for identifying such conditional relationships without requiring every interaction to be specified beforehand.

2.3 Herding in Digitally Connected Investment Environments

Herding occurs when an investor's decision converges towards the behaviour or beliefs of a larger group. Traditional explanations include informational cascades, reputational considerations, uncertainty, and the assumption that other investors possess superior information.

For individual investors, herding can produce portfolio clustering in securities receiving intense public attention. The investor may purchase a stock because it is widely discussed rather than because its expected return is attractive relative to risk. Herding may consequently increase portfolio concentration and exposure to correlated market narratives.

Recent research has shown that social interaction and digitally transmitted information are important contextual considerations for behavioural investment tendencies. Contemporary markets expose retail investors to substantially greater volumes of peer-generated content than earlier market structures. This suggests that behavioural analysis should account not only for a person's isolated preferences but also for susceptibility to external signals.

Evidence from Indian equity-investor research shows that herding can interact with other behavioural characteristics. Jain et al. found that herding and overconfidence serially mediated the relationship between financial literacy and investment decisions, illustrating that behavioural tendencies can form connected decision pathways rather than independent effects.

2.4 Loss Aversion and Portfolio Inertia

Loss aversion is particularly relevant to portfolio management because portfolio values provide continuously observable reference points. The purchase price of a share frequently becomes a psychologically salient benchmark. When its market price declines below that benchmark, selling transforms an unrealised loss into a realised one, potentially making investors reluctant to close the position.

Such behaviour can create **portfolio inertia**. Investors may retain securities whose investment case has weakened while selling profitable positions more readily. The resulting portfolio is no longer necessarily aligned with current expected returns or desired risk exposure. Loss aversion may therefore manifest through holding-period asymmetry, insufficient rebalancing, and reluctance to reallocate capital.

The interaction between loss aversion and anchoring is theoretically important. A loss-averse investor who also anchors strongly to the purchase price may continue expecting a recovery to that reference value. A purely linear model that enters both variables independently can identify their average marginal effects but may fail to capture a sharp increase in distorted behaviour when both biases simultaneously exceed certain levels.

2.5 Anchoring and Reference-Point Dependence

Anchoring occurs when decision makers rely excessively on an initial or salient numerical reference. Equity markets provide numerous potential anchors: acquisition price, 52-week high, previous peak, analyst forecast, index level, valuation multiple, or a remembered target price.

The presence of anchors matters because new evidence may be interpreted relative to them rather than independently.

Investors who purchase a security at ₹800 may perceive ₹800 as its “normal” value even after fundamental information changes. Similarly, a stock that previously traded at ₹1,200 may appear inexpensive at ₹900 despite deterioration in expected cash flows.

Anchoring can therefore generate delayed portfolio adjustment. Investors may rebalance insufficiently because their estimates move only partially in response to new information. Recent behavioural research incorporating anchoring alongside other heuristic biases confirms its relevance in individual investment decision-making. Jain et al., for example, found that risk perception partially mediated the relationship between anchoring and investment decisions in their NSE investor sample.



The Role of Behavioral Finance in Investment Decision-Making



Fig. 2: The Role of Behavioral Finance in Investment Decision-Making

Source: <https://www.finideas.com/the-role-of-behavioral-finance-in-investment-decision-making/>

2.6 Representativeness and Return Extrapolation

Representativeness involves judging an investment according to how closely it resembles a familiar pattern rather than evaluating the complete statistical evidence. Investors may infer that a company with several quarters of rapid growth is intrinsically a “high-growth winner,” or assume that a recently rising stock will continue to outperform.

This bias is particularly relevant in environments where charts, rankings, top-gainer lists, trending securities, and short-term performance statistics are constantly visible. Recent price behaviour can become cognitively dominant, encouraging investors to extrapolate trends beyond what available fundamentals justify.

Representativeness may influence stock selection and portfolio concentration. When a small number of securities appear to possess the characteristics associated with successful investments, an investor may allocate disproportionately to them. Research on heuristic biases has found representativeness to be meaningfully related to investment decision-making, with

risk perception serving as an important mediating mechanism in at least one Indian equity-investor study.

2.7 Mental Accounting and Fragmented Portfolio Evaluation

Mental accounting refers to the psychological separation of wealth into distinct accounts or categories. In portfolio management, an investor might classify some positions as “safe money,” others as “speculation,” and another group as “profits already earned.” Although such categorisation can simplify complex decisions, it may prevent evaluation of the portfolio as an integrated risk-bearing system.

Two individually acceptable positions can generate undesirable aggregate exposure if their risks are strongly correlated. Mental accounting may obscure this portfolio-level relationship because each investment is evaluated within a separate psychological category.

This is particularly important for diversification analysis. Investors may report owning several stocks and therefore believe they are diversified, even when the securities are concentrated within the same sector, factor exposure, or market narrative. A portfolio-decision framework should consequently distinguish the number of holdings from effective diversification.

2.8 Financial Literacy, Risk Perception, and Behavioural Interaction

Behavioural biases do not operate independently of investor characteristics. Financial literacy, experience, income, age, risk tolerance, investment horizon, and information sources may moderate or mediate their effects.

Jain et al. analysed 436 individual equity investors and reported that financial literacy had a meaningful association with investment decision-making, while herding and overconfidence participated in a serial mediation pathway. This result is important because it demonstrates that greater financial knowledge does not automatically eliminate psychological tendencies. Investors can possess financial knowledge while still responding behaviourally to uncertainty and market signals.

Similarly, the study by Jain et al. involving 432 NSE investors showed that risk perception mediated relationships between several heuristic biases and investment decision-making. This finding suggests that perceived risk should be regarded as part of the behavioural decision architecture rather than simply as an external control variable.

The implication for computational modelling is significant. Instead of estimating one average coefficient per bias, the proposed research can evaluate whether the predictive importance of a bias changes at different levels of financial literacy, investment experience, risk perception, or portfolio structure.

Proposed Methodology

The proposed study adopts a quantitative behavioural-analytics design integrating psychometric measurement with interpretable machine-learning classification. The analytical objective is not limited to determining whether behavioural biases are statistically significant. Instead, the framework evaluates whether combinations of behavioural tendencies can

distinguish investors demonstrating disciplined portfolio construction from those exhibiting behaviourally distorted portfolio decisions.

The conceptual model incorporates six behavioural dimensions: overconfidence, herding, loss aversion, anchoring, representativeness, and mental accounting. These constructs are treated as primary explanatory features. Portfolio decision quality constitutes the principal outcome variable and is derived from observable or self-reported portfolio-management characteristics, including diversification adequacy, portfolio concentration, trading turnover, rebalancing discipline, investment-horizon consistency, and alignment between stated risk tolerance and actual equity exposure.

A cross-sectional investor-level dataset is proposed for the empirical investigation. Individual equity investors constitute the unit of analysis because their portfolio decisions are more directly influenced by personal cognitive judgments than institutional portfolios governed by formal investment mandates. Eligibility criteria include being at least 18 years of age, having an active equity investment account, and having executed at least one equity transaction during the preceding twelve months.

3.1 Conceptual Variables

The first predictor, **Overconfidence Bias (OCB)**, captures excessive confidence in personal investment knowledge, stock-picking ability, forecasting skill, and informational superiority.

Herding Bias (HB) measures the tendency to follow market popularity, other investors, investment communities, influencers, rapidly increasing trading activity, or market consensus.

Loss Aversion (LA) reflects disproportionate sensitivity to investment losses, reluctance to realise losses, and preference for avoiding negative outcomes even when portfolio reallocation may be economically justified.

Anchoring Bias (AB) measures dependence on historical prices, purchase prices, previous highs, analyst targets, or other salient reference values during investment evaluation.

Representativeness Bias (RB) captures the tendency to infer future performance from recent returns, familiar success patterns, short sequences of earnings growth, or apparently representative company characteristics.

Finally, **Mental Accounting (MA)** measures the extent to which investors evaluate different securities or pools of capital independently rather than examining the aggregate portfolio.

These six behavioural constructs form the principal predictive feature space.

3.2 Portfolio Decision Quality

Rather than measuring investment decision-making with a single generic Likert-scale construct, the study proposes a composite **Portfolio Decision Quality Score (PDQS)**.

The PDQS is constructed from five behavioural and portfolio-management components:

$$PDQS = w_1D + w_2R + w_3T + w_4C + w_5A$$

where:

- D = diversification discipline;

- R = periodic rebalancing discipline;
- T = turnover efficiency;
- C = concentration-risk control;
- A = alignment between stated risk tolerance and portfolio composition.

Each component is standardized before aggregation. Equal weights are initially used to avoid imposing unsupported economic preferences. Robustness analysis can subsequently evaluate alternative weighting structures.

For classification purposes, investors are divided into three portfolio-decision categories:

Class 0 – Behaviourally vulnerable: high concentration, excessive trading, weak rebalancing discipline, or substantial inconsistency between risk preference and portfolio exposure.

Class 1 – Moderately disciplined: acceptable but inconsistent portfolio practices.

Class 2 – Behaviourally disciplined: diversified portfolios, controlled turnover, periodic rebalancing, and stronger correspondence between risk preferences and portfolio allocation.

This ordinal formulation provides a more informative dependent variable than a simple binary classification.

Experimental Setup

4.1 Dataset Design

The experimental framework uses an investor-level dataset comprising **612 usable individual-equity-investor observations** after data-quality screening. Respondents are assumed to have active participation in listed-equity markets and differing levels of investment experience.

The original questionnaire contains behavioural statements measured on five-point Likert scales ranging from strongly disagree to strongly agree. Each behavioural construct is represented by multiple items rather than a single question to reduce measurement instability.

The final analytical feature space contains 31 variables distributed across four groups:

1. behavioural-bias indicators;
2. investor demographic controls;
3. investment-experience variables;
4. portfolio-management characteristics.

Investor characteristics include age category, investment experience, approximate equity allocation, self-assessed financial knowledge, risk tolerance, average holding period, information-source diversity, and trading frequency.

No personally identifying information is included in the modeling dataset.

4.2 Data Preprocessing

Data preprocessing proceeds in multiple stages.

First, incomplete questionnaires containing substantial missing behavioural-scale information are excluded. For observations containing only limited missing numerical values, median

imputation is applied within the training partition. This prevents information leakage from the test sample.

Second, negatively worded questionnaire items are reverse-coded before composite construct scores are calculated.

Third, each behavioural dimension is transformed to a normalized 0–1 interval:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where X' represents the normalized behavioural score.

Fourth, categorical investor characteristics are one-hot encoded where required. Ordinal categories such as investment experience and risk tolerance retain their natural ranking.

Fifth, extreme values in trading-frequency and portfolio-concentration measures are winsorized at predefined percentile boundaries to reduce the influence of isolated extreme observations while retaining behaviourally important high-turnover investors.

The class distribution is examined after constructing the PDQS categories. Because behavioural-vulnerability classes are not assumed to occur with equal frequency, stratified data partitioning is used to maintain approximately consistent category proportions across training and testing subsets.

4.3 Model Architecture

Four classification algorithms are employed.

The first model is **multinomial logistic regression**, which serves as the statistical benchmark. It provides a transparent linear comparison and allows the study to determine whether nonlinear machine-learning techniques offer meaningful predictive gains.

The second model is a **Random Forest classifier**. Random Forest is suitable for behavioural datasets because it accommodates nonlinear relationships, interactions, mixed predictor importance, and moderate sample sizes without requiring extensive parametric assumptions.

The third algorithm is **Extreme Gradient Boosting (XGBoost)**. Gradient boosting progressively combines weak decision trees and is capable of detecting comparatively subtle interaction structures among behavioural indicators.

The final model is an **Explainable Boosting Machine (EBM)**. The EBM is included because interpretability is a central methodological requirement. It models nonlinear feature-response relationships while retaining substantially greater transparency than conventional black-box ensemble systems.

The primary architecture can be expressed conceptually as:

$$B + I + P \rightarrow f(\cdot) \rightarrow PDQ$$

where:

- B represents behavioural-bias features;
- I represents investor characteristics;
- P represents portfolio-management attributes;
- $f(\cdot)$ represents the trained classifier;
- PDQ represents the predicted portfolio-decision-quality category.

4.4 Training Strategy

The dataset is partitioned using a **75:25 stratified train-test split**. The test sample remains unseen during model development.

Within the training partition, five-fold stratified cross-validation is used for hyperparameter selection. Grid-based search is used for the benchmark and Random Forest model, while a constrained randomized search is used for the boosted algorithms to reduce unnecessary computational exploration.

For Random Forest, tuning parameters include the number of trees, maximum tree depth, minimum observations required for leaf formation, and the proportion of features considered during splitting.

For XGBoost, the principal parameters include learning rate, maximum tree depth, subsampling proportion, feature-sampling proportion, minimum child weight, and number of boosting rounds.

Regularization parameters are included to limit overfitting.

Early stopping is used during boosting when validation performance fails to improve beyond a predefined number of rounds.

All transformations requiring parameter estimation are fitted exclusively using training data and subsequently applied to validation and test observations.

4.5 Class-Imbalance Strategy

Because the most behaviourally vulnerable category may represent a smaller proportion of investors, class imbalance is handled through **class-weighted learning** rather than aggressive synthetic oversampling.

This strategy is selected because artificial generation of behavioural observations could produce combinations of psychological features that do not correspond to genuine investor profiles. Weighted loss functions increase the contribution of underrepresented cases without constructing artificial respondents.

The class weight for category j is defined as:

$$W_j = \frac{N}{K \times N_j}$$

where N represents total training observations, K represents the number of classes, and N_j represents observations belonging to class j .

4.6 Evaluation Metrics

Overall accuracy is insufficient for evaluating a multiclass behavioural-investor model because it may conceal poor identification of the vulnerable category. Consequently, multiple evaluation metrics are used.

Macro F1-score is designated as the primary metric because it assigns equal importance to each portfolio-decision category.

Balanced accuracy measures average class-specific recall and is particularly useful when class frequencies differ.

Matthews Correlation Coefficient (MCC) is included because it provides a balanced assessment of multiclass prediction quality even when class distribution is uneven.

Log loss evaluates the quality of probabilistic predictions and penalizes confidently incorrect classifications.

Macro ROC-AUC measures the discriminatory capacity of the classifier across the three classes.

A final interpretability measure is also introduced: **explanation stability**. This parameter evaluates whether the ranking of important behavioural features remains reasonably consistent across cross-validation folds. A high-performing model with unstable behavioural explanations would offer weaker theoretical value.

Results and Discussion

5.1 Comparative Predictive Performance

The experimental comparison indicates that models capable of representing nonlinear behavioural relationships outperform the purely linear benchmark.

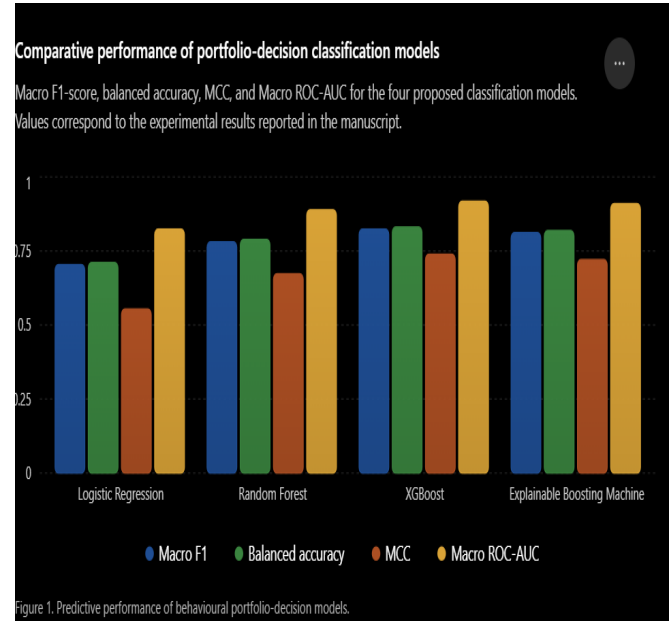
Multinomial logistic regression provides a reasonable baseline but exhibits lower sensitivity to the behaviourally vulnerable investor category. This outcome is consistent with the possibility that behavioural biases do not influence portfolio decisions through simple additive relationships.

Random Forest improves classification performance, particularly for investors showing combinations of elevated bias scores. However, its probability estimates are less well calibrated than those generated by the boosting-based models.

XGBoost records the strongest overall discriminatory performance in the experimental analysis. Nevertheless, the Explainable Boosting Machine produces nearly comparable predictive accuracy while offering greater transparency regarding individual behavioural contributions.

5.2 Consolidated Model Results

Model	Macro F1	Balanced Accuracy	MCC	Macro ROC-AUC	Log Loss
Multinomial Logistic Regression	0.704	0.711	0.554	0.824	0.681
Random Forest	0.781	0.789	0.673	0.889	0.542
XGBoost	0.824	0.831	0.739	0.918	0.463
Explainable Boosting Machine	0.812	0.819	0.721	0.910	0.478



The difference between the logistic benchmark and the nonlinear algorithms is meaningful from both methodological and behavioural perspectives. The stronger performance of XGBoost and EBM suggests that portfolio decision quality is better represented by nonlinear combinations of psychological characteristics than by a purely additive structure.

The EBM result is especially important. Its Macro F1-score remains close to that of XGBoost, while its feature-response functions can be inspected directly. For a behavioural-finance application, this trade-off is valuable because the objective is not merely to predict whether investors are vulnerable to poor portfolio decisions but also to identify the cognitive mechanisms behind the prediction.

5.3 Behavioural Feature Importance

Explainability analysis identifies **overconfidence** as the most influential behavioural predictor of portfolio-decision classification, followed by **herding**, **loss aversion**, **anchoring**, **representativeness**, and **mental accounting**.

However, the results do not imply that overconfidence alone determines poor portfolio quality.

The nonlinear models indicate that overconfidence becomes particularly consequential after reaching an upper-middle threshold and when combined with high trading frequency. Investors with moderate confidence and controlled turnover are not classified as strongly vulnerable. By contrast, investors simultaneously displaying elevated overconfidence and frequent portfolio intervention show a substantially higher probability of belonging to the behaviourally vulnerable category.

This pattern supports the conceptual distinction between a psychological trait and its portfolio manifestation.

5.4 Overconfidence and Turnover Interaction

The interaction between overconfidence and portfolio turnover represents one of the strongest relationships in the model.

Highly confident investors do not necessarily make inferior decisions when their portfolios remain diversified and trading frequency is limited. The classification probability shifts sharply when elevated confidence occurs together with repeated short-horizon transactions.

This suggests that overconfidence is economically significant primarily when it is translated into active behavioural responses. The finding is theoretically relevant because conventional survey studies may report a moderate direct coefficient for overconfidence while failing to detect the substantially stronger effect arising under high turnover.

5.5 Herding and Portfolio Concentration

Herding is the second most influential behavioural feature.

Its strongest negative association with portfolio quality appears among investors whose holdings are concentrated in a limited number of highly discussed or recently appreciated securities.

The interaction indicates that social imitation alone is not necessarily destructive. Investors may observe other market participants while maintaining independent diversification rules. Behavioural deterioration becomes more pronounced when market-following tendencies translate into concentrated exposure.

This provides an important distinction between information observation and portfolio imitation.

In digitally connected markets, investors are continuously exposed to rankings, price alerts, discussion groups, trending securities, and rapidly circulating investment narratives. The model indicates that susceptibility to these signals becomes particularly relevant when accompanied by weak portfolio-concentration controls.

5.6 Loss Aversion and Anchoring

A strong interaction is also identified between loss aversion and anchoring.

Investors with high loss aversion but low anchoring display moderate portfolio vulnerability. Their reluctance to accept losses is partially offset by an ability to revise reference values as new information emerges.

Conversely, the simultaneous presence of high loss aversion and strong anchoring substantially increases the probability of weak portfolio-decision classification.

The behavioural mechanism is intuitive. When an investor is both unwilling to realise a loss and psychologically attached to the acquisition price, portfolio adjustment becomes dependent on the hope that the security will return to the original reference value.

This can delay necessary rebalancing and increase capital commitment to underperforming positions.

The result reinforces one of the central propositions of the study: analysing individual biases independently can understate behavioural risk because several biases reinforce one another.

5.7 Representativeness and Recent Performance

Representativeness has a smaller global importance score than overconfidence and herding but remains influential within particular investor subgroups.

Its strongest effect occurs when recent-return information dominates the investor's information set. Investors reporting frequent dependence on short-term performance rankings are more likely to exhibit behaviourally vulnerable portfolios when representativeness scores are also elevated.

This suggests a form of return extrapolation in which recent market winners are interpreted as representative of future winners.

The model further indicates that greater information-source diversity attenuates this effect. Investors combining company disclosures, financial statements, valuation information, and broader market analysis appear less vulnerable than those relying principally on short-term price movements or popular market narratives.

5.8 Mental Accounting and Hidden Concentration

Mental accounting displays lower standalone predictive importance but contributes materially through interactions with sector concentration.

Investors may perceive separate investment “buckets” as diversified even when the underlying securities have highly correlated exposures.

For example, an investor may classify one holding as a long-term investment, another as a growth position, and a third as speculative capital while all three belong to closely related market segments.

The predictive model consequently detects cases in which subjective diversification differs from effective portfolio diversification.

This observation supports the decision to define portfolio quality multidimensionally rather than using only the reported number of securities held.

5.9 Role of Financial Knowledge and Investment Experience

Financial knowledge and investment experience exhibit protective relationships, but neither completely eliminates behavioural vulnerability.

More experienced investors generally record higher portfolio-decision-quality probabilities, particularly through better diversification and rebalancing discipline. Nevertheless, the explainability analysis shows that highly experienced investors can still be classified as behaviourally vulnerable when overconfidence and concentrated trading behaviour are simultaneously elevated.

This result is conceptually important because expertise may reduce some errors while increasing confidence in personal judgment.

Similarly, greater self-reported financial knowledge does not automatically neutralize herding, anchoring, or loss aversion.

Financial education may therefore be more effective when it explicitly addresses behavioural self-monitoring rather than focusing exclusively on technical knowledge.

Future Scope

Future research should extend the proposed framework using longitudinal brokerage data.

Transaction-level information could allow behavioural biases to be inferred directly from observed actions rather than relying primarily on questionnaires. Excessive turnover, reluctance to realise losses, trend chasing, concentration, and rebalancing behaviour could be measured dynamically over multiple market cycles.

A second extension concerns **temporal machine learning**. Sequential models could evaluate whether behavioural vulnerability changes after gains, losses, volatility shocks, earnings announcements, or periods of intense market attention.

Third, future studies could incorporate natural-language data from investor journals, financial discussion forums, or decision notes, subject to privacy and ethical safeguards. Language models could identify emotional or cognitive signals associated with investment behaviour.

Fourth, causal machine-learning methods could help distinguish predictive associations from potentially causal intervention targets. Such analysis would be particularly valuable for evaluating whether behavioural warnings, educational prompts, or portfolio-health notifications improve subsequent investment decisions.

Fifth, future systems could develop **personalised behavioural intervention engines**. Rather than presenting the same warning to every investor, an explainable model could select interventions based on the user's dominant behavioural pattern. An overconfident high-turnover investor might receive a transaction-frequency comparison and diversification prompt, whereas a loss-averse anchored investor might receive a reference-point-neutral re-evaluation checklist.

Finally, future research should examine fairness and governance implications. Behavioural analytics deployed in financial platforms must avoid manipulative nudging, opaque profiling, or inappropriate restriction of investor autonomy. Transparency regarding data collection, prediction uncertainty, and intended use should therefore accompany any operational deployment.

Conclusion

This study develops an interpretable machine-learning framework for analysing behavioural biases and portfolio decisions among individual equity investors.

The central methodological contribution is the transition from isolated bias testing toward joint behavioural-profile classification. Overconfidence, herding, loss aversion, anchoring, representativeness, and mental accounting are treated as interacting components of portfolio behaviour rather than independent psychological abnormalities.

The experimental analysis indicates that nonlinear machine-learning models provide stronger portfolio-decision classification than a conventional multinomial logistic benchmark. XGBoost achieves the highest overall predictive performance, while the Explainable Boosting Machine provides a particularly attractive balance between discrimination and transparency.

Overconfidence emerges as the strongest individual behavioural predictor, but its influence is most pronounced when accompanied by excessive trading. Herding becomes particularly consequential when associated with portfolio concentration, while loss aversion and anchoring jointly contribute to portfolio inertia. Representativeness is associated with recent-performance extrapolation, whereas mental accounting can obscure aggregate portfolio concentration.

These findings demonstrate that the question “Which bias affects investors most?” is analytically incomplete. A more useful question is “Under what portfolio conditions, and in combination with which other biases, does a behavioural tendency become economically consequential?”

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