

# **Artificial Intelligence and Behavioural Finance: A Review of Investor Biases, Algorithmic Decision-Making, and Emerging Opportunities**

## *Authors Details*

**Bhawandeep Singh<sup>1\*</sup>**

Department of Commerce, Akal University, Talwandi Sabo, Punjab.

**Corresponding Author:** *deepbhawan.dhalio@gmail.com*

**ABSTRACT:** Behavioural finance explains why investors do not always act as perfectly rational decision-makers. Emotions, mental shortcuts, social influence and the way information is presented can shape investment choices, sometimes leading to decisions that differ from an investor's long-term interests. At the same time, artificial intelligence (AI)—including machine learning, natural language processing, recommendation systems and robo-advisory tools—is changing how financial information is collected, interpreted and presented. This review examines the intersection of AI and behavioural finance, with particular attention to investor biases, sentiment analysis, algorithmic advice, personalised financial services and the Indian investment setting. Drawing on foundational behavioural-finance theories and recent research on robo-advisors, AI-based investment management and technology-mediated investor behaviour, the paper organises the literature into five themes: detecting behavioural patterns, supporting disciplined decisions, personalisation and trust, the possibility of technology amplifying biases, and governance. The review suggests that AI can help identify patterns such as herding, overconfidence and loss aversion, but prediction should not be confused with understanding or eliminating bias. Data quality, opacity, privacy, unequal digital access and conflicts of interest remain important concerns. The paper proposes an integrated conceptual framework linking investor characteristics, AI system design, behavioural mechanisms and decision outcomes.

It concludes with a research agenda for India, including studies of retail investors, digital trading platforms, financial literacy, language diversity and human–AI advice. The paper is a narrative integrative review and does not claim a new empirical dataset or a fully exhaustive systematic search.

**Keywords:** *Behavioural finance; artificial intelligence; investor behaviour; machine learning; robo-advisors; behavioural biases; sentiment analysis; India.*

## 1. Introduction

Financial decisions are often described through the language of risk, return and rational choice. In practice, investors are human beings who interpret information through their experience, expectations, emotions and social surroundings. A sudden fall in share prices may lead one investor to sell immediately, while another may hold the investment because of a long-term plan. Similarly, a rapidly rising stock may attract buyers even when its valuation is difficult to justify. These differences are central to behavioural finance, which studies how psychological and social factors influence financial decisions.

The growth of digital finance has added a new layer to this discussion. Investors now receive market updates through mobile applications, social media, online communities, algorithmic recommendations and automated portfolio services. AI systems can process large volumes of market data, detect patterns, classify news sentiment and tailor information to individual users. Such capabilities may support better-informed decisions. However, technology is not automatically neutral. A recommendation engine may reinforce an investor's existing beliefs, a trading interface may encourage frequent activity, and a model trained on past behaviour may reproduce patterns that were already biased.

The relationship between AI and behavioural finance is therefore two-sided. AI can act as a behavioural support mechanism by identifying risk-taking patterns, reminding users of their stated goals and presenting information in a structured manner. On the other hand, AI-enabled platforms can intensify emotional reactions through personalised notifications, persuasive design or rapid feedback. In addition, the algorithm itself may contain assumptions and biases introduced through data selection, model design or business incentives.

This review brings these issues together in an accessible framework. It focuses not merely on whether AI can forecast prices, but on how AI interacts with the person making the investment decision. The Indian context is relevant because retail participation increasingly takes place through digital platforms, while investors differ widely in financial knowledge, income, language, access and risk capacity. A technology that works for an experienced investor may not be understood in the same way by a first-time participant.

### **1.1 Objectives of the Study:**

- To explain the main behavioural-finance concepts relevant to AI-supported investment decisions.
- To review how AI techniques are used to detect, interpret or respond to investor behaviour.
- To examine the opportunities and limitations of robo-advisors and AI-enabled investment platforms.
- To identify ethical, regulatory and practical concerns, with specific attention to India.
- To propose a conceptual framework and future research directions.

## **2. Review of Literature**

### **2.1 Introduction**

Behavioural finance has emerged as an important area of financial research by explaining how psychological, emotional and social factors influence investment decisions. Unlike traditional financial theories, which generally assume that investors make rational decisions based on available information, behavioural finance recognises that investors may be influenced by cognitive biases, emotions, personal experiences and market sentiment. The pioneering works of Kahneman and Tversky (1979), Tversky and Kahneman (1974), and Thaler (1985) established the theoretical foundation for understanding these behavioural patterns.

With the advancement of artificial intelligence (AI), the study of investor behaviour has entered a new phase. AI technologies, including machine learning, natural language processing, predictive analytics and robo-advisory systems, are increasingly being used to analyse financial information and support investment decisions. These technologies offer

opportunities to identify behavioural patterns, understand market sentiment and provide personalised investment guidance.

However, the relationship between AI and behavioural finance is not entirely straightforward. Although AI can assist investors in making structured and informed decisions, it may also reinforce existing biases through algorithmic recommendations, excessive reliance on automated advice and technology-driven trading behaviour. Therefore, the existing literature needs to be examined from both technological and behavioural perspectives.

This review discusses the theoretical foundations of behavioural finance, the development of AI-based financial services, the role of AI in addressing investor biases, and the emerging opportunities and challenges associated with AI-supported investment decisions.

## **2.2 Theoretical Foundations of Behavioural Finance**

### **2.2.1 Prospect Theory and Loss Aversion**

Kahneman and Tversky (1979) introduced Prospect Theory to explain how individuals make decisions under conditions of uncertainty. The theory suggests that people evaluate financial outcomes relative to a reference point and often experience losses more strongly than equivalent gains. This tendency, known as loss aversion, may influence investors to avoid certain risks or hold declining investments in the hope of recovering their original investment.

Shefrin and Statman (1985) examined the disposition effect, which refers to investors' tendency to sell profitable investments too early while continuing to hold investments that are making losses. Odean (1998) further investigated this behaviour and demonstrated how reluctance to realise losses can affect investment decisions.

These studies provide a useful foundation for examining whether AI-based investment tools can help investors manage emotional reactions. Automated portfolio rebalancing, risk alerts and structured investment recommendations may help reduce impulsive decisions. However, the effectiveness of such tools depends on the quality of their design and the extent to which investors understand and trust the recommendations.

### **2.2.2 Heuristics and Cognitive Biases**

Tversky and Kahneman (1974) explained that individuals often rely on mental shortcuts, known as heuristics, when making decisions under uncertainty. Although these shortcuts simplify complex situations, they can lead to systematic errors in judgement.

Barberis and Thaler (2003) reviewed the major developments in behavioural finance and highlighted the importance of psychological factors in explaining financial market behaviour. Their work demonstrated how cognitive limitations and psychological tendencies can contribute to market anomalies and deviations from traditional rational-choice assumptions.

Barber and Odean (2000) examined the trading behaviour of individual investors and found that frequent trading was associated with poorer investment performance in their sample. Their later work also discussed the role of overconfidence in individual investment decisions (Barber & Odean, 2001).

These findings are relevant to AI-based financial services because machine learning can examine transaction patterns and identify behaviours that may be associated with excessive trading, overconfidence or other behavioural tendencies. However, identifying a pattern does not automatically establish the psychological reason behind it.

### **2.2.3 Mental Accounting and Investor Psychology**

Thaler (1985) introduced the concept of mental accounting to explain how individuals mentally divide money into different categories and treat each category differently. Investors may distinguish between salary savings, investment profits and inherited money, even though the economic value of money remains the same.

Kahneman and Riepe (1998) discussed the practical implications of investor psychology for portfolio management and financial decision-making. Their work highlighted the need to understand how psychological factors influence risk perception, investment preferences and responses to market movements.

These theoretical contributions suggest that AI-based financial tools should consider not only an investor's financial position but also their goals, risk tolerance, investment experience and decision-making tendencies.

## **2.3 Artificial Intelligence in Financial Decision-Making**

### **2.3.1 Machine Learning and Predictive Analytics**

The application of machine learning in finance has expanded the possibilities for analysing financial data and identifying complex relationships. Gu, Kelly and Xiu (2020) examined the use of machine learning in empirical asset pricing and demonstrated how these methods can be applied to financial prediction and investment analysis.

López de Prado (2018) discussed advanced machine learning methods for financial applications, including the importance of appropriate model validation and the management of data-related problems. These contributions indicate that AI can support financial analysis by processing large datasets and identifying patterns that may not be easily recognised through conventional methods.

From a behavioural finance perspective, machine learning can be used to examine trading frequency, portfolio concentration, investment reactions to market fluctuations and changes in investor activity. Such applications may help researchers identify patterns associated with behavioural biases. However, predictive accuracy alone cannot establish whether an investor's decision was rational or irrational.

### **2.3.2 Natural Language Processing and Sentiment Analysis**

Natural language processing has become an important tool for analysing financial news, corporate announcements, online discussions and investor opinions. Sentiment analysis enables researchers to examine whether financial communication reflects positive, negative or neutral attitudes.

Tetlock (2007) investigated the relationship between media content and stock market behaviour, highlighting the relevance of media sentiment in understanding financial markets. Loughran and McDonald (2011) examined the challenges of analysing financial language and demonstrated the importance of using context-appropriate terminology.

These studies provide a foundation for applying AI-based sentiment analysis to behavioural finance. By examining financial news and investor discussions, AI systems may help researchers understand how public sentiment, attention and collective reactions relate to market activity.

However, online sentiment does not necessarily represent the views of all investors. Social media discussions may be influenced by misinformation, coordinated activity and the unequal participation of different investor groups. Hence, sentiment analysis should be interpreted alongside other financial and behavioural evidence.

## **2.4 AI-Based Robo-Advisors and Behavioural Finance**

### **2.4.1 Development of Robo-Advisory Services**

Robo-advisors are digital financial services that use algorithms to support investment planning, asset allocation and portfolio management. They generally collect information about users' financial goals, investment horizon and risk preferences before generating recommendations.

Jung et al. (2018) discussed the development of robo-advisory services and their relevance to financial institutions and digital investment management. Brenner and Meyll (2020) examined whether robo-advisors could serve as substitutes for traditional human financial advice, highlighting the importance of understanding investor preferences and the nature of financial advisory relationships.

Cardillo and Chiappini (2024), in their systematic literature review of robo-advisors, identified research streams relating to behavioural issues, performance, classification and algorithmic model development. Their review also highlighted the relevance of robo-advisory services for financial institutions and investment management.

The literature indicates that robo-advisors can make investment services more accessible and support disciplined portfolio management. However, their effectiveness depends on the accuracy of user information, the quality of the underlying algorithms and the ability of the system to accommodate changing financial circumstances.

### **2.4.2 Robo-Advisors and Behavioural Biases**

Lisauskiene and Darskuvienė (2021) examined the relationship between robo-advisors and behavioural biases through an interdisciplinary literature review. Their findings suggest that robo-advisors may support more informed and less biased investment decisions. At the same time, they highlighted the possibility that automated investment processes may reduce investors' active involvement and understanding of financial markets.

Eichler and Schwab (2024) critically examined robo-advisory services from a behavioural finance perspective. Their review identified limitations relating to the personal relationship between advisers and investors, the influence of human judgement on algorithms, the persistence of market risk and the limited ability of robo-advisors to improve financial literacy.

These findings indicate that robo-advisors should not be considered completely free from behavioural influences. While automated systems can reduce some forms of emotional decision-making, they may also introduce new challenges associated with investor trust, limited personalisation and excessive reliance on technology.

## **2.5 Empirical Studies on AI and Behavioural Finance**

Shanmuganathan (2020) examined the relationship between behavioural finance and AI-based investment advisory services through a longitudinal case study of robo-advisors. The study highlighted the growing relevance of AI-based applications in financial advisory services and their potential role in supporting investment decisions.

Bhatia, Chandani and Chhateja (2020) investigated robo-advisory services and their potential to address behavioural biases among investors in India. Their qualitative study involved interviews with industry experts from financial services and technology-related organisations. The findings highlighted the importance of investor awareness, trust-building and accurate risk profiling. The study also noted that robo-advisory services in India required further development to assess retail investors' risk preferences effectively.

Nourallah et al. (2026) conducted a scoping review of financial robo-advisors and identified two broad research streams: asset management and behavioural finance. Their review highlighted the potential of robo-advisors to support investment decisions while identifying concerns about limited personalisation and the use of restricted inputs. The authors also identified financial literacy and technology adoption as areas requiring further investigation.

Taken together, these studies suggest that AI-based financial advisory services have the potential to influence investor behaviour, but their actual impact depends on investor characteristics, service design, financial knowledge and trust in technology.

## 2.6 AI, Investor Trust and Financial Literacy

Trust and financial literacy are important factors influencing the adoption of AI-based financial services. Investors may hesitate to rely on automated recommendations when they do not understand how the system operates or how their personal information is used.

Eichler and Schwab (2024) highlighted the limitations of robo-advisors in addressing financial literacy and the importance of considering investor expectations and trust. Their findings suggest that automated investment services should not be viewed as a complete replacement for human financial guidance.

Similarly, Bhatia et al. (2020) emphasized the need to improve investor awareness and build trust in robo-advisory services in India. Their findings indicate that effective risk profiling and investor education are important for improving the usefulness of automated financial advice.

Financial literacy may influence how investors interpret AI-generated recommendations, understand investment risks and respond to automated guidance. Digital financial literacy is also relevant because users need to understand how digital platforms present information, collect personal data and generate recommendations.

Therefore, the relationship between AI and investment behaviour should be examined not only through technological performance but also through investor awareness, trust and the ability to interpret financial information.

## 2.7 Review Approach and Scope

This paper uses a narrative integrative review approach. It combines foundational works in behavioural economics and finance with research on machine learning in financial markets, sentiment analysis, robo-advisory services and technology adoption. The literature was organised thematically rather than subjected to a quantitative meta-analysis. The review draws on established books and journal articles as well as recent review studies on robo-advisors and AI-enabled investment management. Search terms relevant to the topic include 'behavioural finance', 'investor bias', 'artificial intelligence in finance', 'machine learning', 'sentiment analysis', 'robo-advisor', 'trust in AI' and 'retail investor behaviour'.

The purpose is to synthesise concepts and identify connections, not to claim that every relevant publication has been captured. No original survey, experiment, bibliometric dataset or statistical test was conducted. Consequently, statements in this paper are interpretive summaries of prior work, and proposed relationships should be tested through future empirical research. The references include foundational theory, methodological contributions and recent reviews; readers should verify bibliographic details against publisher records before journal submission.

### **3. Theoretical Foundations of Behavioural Finance**

#### **3.1 Bounded rationality and heuristics**

Traditional models often assume that individuals evaluate available information consistently and select the option that maximises expected utility. Herbert Simon's idea of bounded rationality offers a more practical view: people have limited time, attention and cognitive capacity. Investors therefore rely on shortcuts, or heuristics, to simplify complex choices. These shortcuts can be useful, but they may also create systematic errors. AI tools may reduce information-processing burdens, yet they cannot remove the limits of human attention or guarantee that the inputs are meaningful.

#### **3.2 Prospect theory, loss aversion and framing**

Prospect theory explains that people evaluate outcomes relative to a reference point and often experience losses more strongly than equivalent gains. Loss aversion may lead investors to hold declining assets for too long, avoid reasonable risks after a loss, or sell winning assets too early. Framing also matters: the same investment can appear more attractive when presented as a potential gain rather than a possible loss. An AI interface that displays performance only in positive terms may influence the decision differently from one that shows gains, losses, fees and uncertainty together.

#### **3.3 Overconfidence, anchoring and representativeness**

Overconfidence refers to excessive belief in one's knowledge, judgement or ability to forecast outcomes. It can encourage excessive trading and underestimation of risk. Anchoring occurs when a person relies heavily on an initial number, such as a purchase price or a past high, while representativeness involves judging probabilities through

resemblance to familiar patterns. Algorithms may identify trading behaviour consistent with these biases, but they cannot infer a person's psychological state with certainty from a single transaction.

### **3.4 Herding, social influence and mental accounting**

Herding occurs when investors follow the actions or opinions of others, sometimes without independently assessing the underlying information. Social media and digital investment communities can accelerate the circulation of market narratives. Mental accounting refers to the tendency to treat money differently depending on its source or intended purpose, even when the economic value is the same. AI systems that analyse online discussions may detect collective attention, but popularity is not equivalent to fundamental value or reliable evidence.

## **4. Artificial Intelligence in Financial Decision-Making**

### **4.1 Machine learning and predictive analytics**

Machine learning (ML) uses algorithms that learn statistical relationships from data. In finance, common approaches include regression, decision trees, random forests, support vector machines, gradient boosting and neural networks. These methods are applied to forecasting, classification, fraud detection, portfolio analysis and risk monitoring. In behavioural finance, ML can help identify patterns in transaction histories, investor responses and market activity that may be associated with behavioural tendencies.

Predictive performance must be interpreted carefully. Financial markets are noisy, adaptive and affected by policy decisions, global events and unexpected shocks. A model that performs well in one period may fail when market conditions change. Data leakage, survivorship bias, overfitting and unrealistic transaction-cost assumptions can make back-tested results look stronger than actual performance. A useful behavioural application should therefore report out-of-sample results, uncertainty and the limits of its predictions.

### **4.2 Natural language processing and sentiment analysis**

Natural language processing (NLP) enables computers to process text, including financial news, company disclosures, analyst commentary and public online discussions. Sentiment analysis attempts to classify text as positive, negative or neutral, or to estimate the intensity

of an expressed attitude. Such information may help researchers examine how public mood relates to trading volume, volatility or investor attention.

Financial language is context-dependent. A phrase that appears negative in ordinary conversation may be neutral in a financial report, and sarcasm or regional language can complicate interpretation. Social media data may also over-represent highly active users. In India, multilingual communication and code-switching create additional challenges: investor discussions may combine English with Hindi or other Indian languages. A model trained mainly on English-language data may not represent these conversations accurately.

#### **4.3 Robo-advisors and personalised advice**

Robo-advisors use digital questionnaires, algorithms and portfolio rules to provide investment guidance or automated portfolio management. Depending on the service, they may recommend asset allocations, support rebalancing and provide goal-based projections. The potential benefits include lower service costs, convenience and more consistent implementation of a chosen strategy. Research reviews, however, identify continuing questions about trust, user satisfaction, personalisation, performance and the extent to which automated advice can address behavioural needs.

A questionnaire-based risk profile is only an approximation of an investor's circumstances. Answers may change with recent market experiences, and a person's stated tolerance for loss may differ from their reaction to an actual decline. A robust service should treat risk profiling as an ongoing process, explain the assumptions behind its recommendations and provide a clear route to human support where needed.

#### **4.4 Generative AI and conversational financial tools**

Conversational AI can explain financial terms, summarise documents and help users compare scenarios in accessible language. It may be useful for financial education, especially when explanations are adapted to a learner's level. However, generated answers can contain errors, omit important conditions or sound more certain than the evidence permits. Such tools should not present illustrative scenarios as guaranteed returns or replace regulated advice where that advice is required. Users need clear disclosures about the system's role, data sources and limitations.

## **5. Thematic Synthesis: AI and Investor Biases**

### **5.1 Detecting behavioural patterns**

AI can analyse repeated actions that may signal behavioural tendencies. Frequent buying and selling, concentrated portfolios, repeated reactions to market headlines or persistent avoidance of certain assets can be studied as observable patterns. Yet behaviour does not prove a bias. High trading frequency may reflect a professional strategy, liquidity needs or portfolio rebalancing rather than overconfidence. Researchers should combine transaction data with contextual information and validated behavioural measures.

A sound research design can distinguish between the detection of an event and the interpretation of its cause. For example, an algorithm may flag that an investor repeatedly sells after a price decline. A follow-up survey or experiment can explore whether the action reflects loss aversion, a change in financial needs or a rational response to new information. This mixed approach can reduce the risk of assigning psychological labels based only on machine-generated classifications.

### **5.2 Supporting disciplined decisions**

AI-based decision aids may help investors follow a pre-agreed plan. A platform can show the difference between a current allocation and a target allocation, display the impact of fees, or ask a user to review a decision before placing an order. It may also provide reminders about diversification and time horizon. Such features can create a pause between an emotional impulse and an irreversible action.

The design of these prompts is important. Too many alerts can create fatigue, while strongly worded messages may pressure users. Behavioural support should be transparent and should allow investors to understand why a prompt appears. It should also avoid treating every deviation from a plan as irrational, since a person's financial circumstances can change.

### **5.3 Personalisation, trust and perceived control**

Personalisation can make financial information more relevant by considering a user's goals, knowledge and preferred communication style. At the same time, personalisation raises questions about how much data is collected and whether the system uses sensitive

inferences. Trust is influenced not only by perceived accuracy but also by transparency, reliability, security, accountability and the availability of human assistance.

Some users may prefer a human adviser because financial decisions involve anxiety, family obligations and life events that are difficult to capture in a form. Others may value the speed and privacy of a digital tool. The literature does not support assuming that one mode of advice is suitable for every investor. Hybrid arrangements, in which AI handles routine analysis and humans support complex or emotionally demanding decisions, deserve further evaluation.

#### **5.4 Technology can amplify rather than reduce bias**

AI systems are shaped by the data and objectives used to develop them. If a platform optimises engagement or transaction frequency, its design may encourage activity that does not serve the investor's long-term interests. Recommendation systems may create feedback loops: a user clicks on a particular type of content, the system supplies more of it, and the user's attention becomes increasingly concentrated. Similar loops can emerge when a model interprets past risk-taking as a stable preference.

Algorithmic advice can also create automation bias, where users accept a system's recommendation because it appears technical or objective. Conversely, users may reject useful advice because they do not understand how it was generated. Explainability should therefore be practical: investors should receive understandable reasons, relevant assumptions, major risks and information about when the model may be unreliable.

#### **5.5 Market sentiment and collective behaviour**

Sentiment analytics can help examine the relationship between public attention and market movements. Sudden growth in discussion around a company or asset may coincide with increased trading activity. However, attention measures can be distorted by bots, coordinated campaigns, reposting and platform-specific demographics. Sentiment should be treated as one input among many, not as a direct measure of investor belief or a standalone basis for investment decisions.

### **6. Opportunities and Risks in the Indian Context**

India offers a meaningful setting for studying AI and behavioural finance because retail investing is increasingly mediated by digital interfaces, while users differ in financial

literacy, access to advice, language and familiarity with market risk. Digital tools may make basic financial information and portfolio services easier to access. They may also expose new investors to rapid price updates, social-media narratives and simplified trading experiences that can encourage short-term attention.

For Indian investors, financial decisions are connected with household responsibilities, education expenses, housing, retirement planning and preferences for familiar savings products. Risk capacity and risk tolerance should not be treated as identical. A person may express willingness to take risk but lack the financial capacity to absorb a loss. AI systems should therefore distinguish investment goals, liquidity requirements, time horizon and the consequences of adverse outcomes.

Language inclusion is another important issue. Financial education and disclosures need to be understandable across linguistic communities. Translation alone may not capture local expressions, financial practices or the meaning of risk-related terms. Testing AI tools with diverse users can reveal whether explanations are understood and whether certain groups are more likely to misinterpret recommendations.

Consumer protection, privacy and responsible data use should be built into the design of AI-enabled financial services. Data collection should be proportionate to the service, and users should be informed about how their information is used. Providers should make charges, conflicts of interest, model limitations and complaint channels clear. Human review and accessible grievance mechanisms are particularly relevant when automated outputs affect consequential financial decisions.

## **7. Integrated Conceptual Framework**

The review proposes a framework in which four sets of factors interact: (1) investor characteristics, including financial literacy, experience, goals, risk capacity and psychological tendencies; (2) AI system characteristics, including data quality, personalisation, explainability, interface design and optimisation objectives; (3) behavioural mechanisms, including attention, framing, trust, social influence and emotional response; and (4) decision outcomes, such as diversification, trading frequency, adherence to goals, perceived control and financial well-being.

The proposed relationship is not a simple direct path from AI adoption to better decisions. Investor characteristics influence how a system is interpreted, while system design shapes what information becomes salient. Behavioural mechanisms mediate the relationship between AI exposure and decision outcomes. Financial literacy, trust, market conditions and access to human advice may moderate these relationships. Feedback loops also matter: decisions generate new data, which may influence future recommendations.

**Investor characteristics → AI design and information → Behavioural mechanisms → Investment decisions**

↑ \_\_\_\_\_ feedback and learning \_\_\_\_\_ ↓

## 7.1 Propositions for future testing

- P1: Clear explanations and transparent uncertainty disclosures are associated with greater informed understanding of AI-generated investment guidance.
- P2: Behavioural prompts may reduce impulsive actions when they are timely, relevant and aligned with the investor's stated goals.
- P3: The relationship between AI personalisation and decision quality is mediated by perceived relevance and moderated by trust and financial literacy.
- P4: Engagement-focused interface features may increase trading activity, particularly among users who are highly responsive to social cues.
- P5: Access to human support may strengthen users' ability to interpret AI recommendations in complex or emotionally demanding situations.
- P6: Language accessibility and locally validated explanations are associated with better comprehension among diverse Indian investor groups.

## 8. Research Gaps and Future Agenda

### 8.1 Measuring bias with appropriate evidence

Future studies should avoid treating trading outcomes as direct psychological measures. Researchers can combine validated scales, controlled experiments, transaction records and interviews. Longitudinal designs can examine whether a behavioural pattern persists or changes after market events. Where possible, researchers should preregister hypotheses and report alternative explanations, missing data and robustness checks.

## **8.2 Comparing human, AI and hybrid advice**

Comparative studies can examine how investors respond to advice from a human adviser, a fully automated system and a hybrid service. Outcomes should include not only returns but also comprehension, confidence calibration, adherence to goals, perceived fairness, complaints and user well-being. Studies should distinguish short-term satisfaction from long-term decision quality.

## **8.3 Responsible experimentation and evaluation**

Field experiments may test whether a neutral risk reminder, a cooling-off prompt or a clearer fee display changes decision-making. Such experiments must protect participants from avoidable financial harm and should not manipulate vulnerable users into risky activity. Researchers should report unintended effects, including alert fatigue, disengagement and overreliance on automation.

## **8.4 Indian retail-investor research**

Research in India can examine how age, income, experience, location, language and digital familiarity relate to trust and use of AI-based financial tools. Samples should not be limited to urban, English-speaking platform users. Researchers can compare first-time investors with experienced participants and examine whether financial education changes how AI explanations are understood. Qualitative interviews may reveal concerns that standard survey questions miss.

## **8.5 Explainability, fairness and governance**

More work is required on practical explainability: what information helps investors understand an algorithm without overwhelming them? Fairness audits should consider whether recommendation quality or error rates differ across demographic and linguistic groups. Governance research should examine accountability when an automated recommendation causes harm, how model changes are documented, and how users can challenge or appeal a decision.

## 9. Practical Implications

- **For investors:** treat AI output as decision support, review assumptions and charges, compare advice with personal goals, and avoid interpreting a forecast as a guarantee.
- **For financial service providers:** prioritise understandable explanations, suitability checks, privacy safeguards, clear fee disclosure and accessible human assistance.
- **For educators:** teach common behavioural biases alongside digital financial literacy, including how recommendation systems and online attention can shape choices.
- **For researchers:** distinguish predictive accuracy from causal explanation, validate measures across user groups and disclose data and model limitations.
- **For policymakers and supervisors:** consider auditability, consumer disclosures, complaint resolution, data governance and safeguards against interface designs that exploit behavioural vulnerabilities.

## 10. Limitations

This paper is a narrative integrative review rather than a systematic review with a registered protocol and reproducible screening flow. It does not report a complete database search, article-level quality appraisal, meta-analysis or original empirical findings. The field is changing rapidly, and AI products differ considerably in their data, design and intended use. Findings from one country, platform or investor group may not transfer directly to another. The proposed framework and propositions are conceptual and require empirical testing.

## 11. Conclusion

Artificial intelligence and behavioural finance are closely connected because investment decisions depend on both information processing and human judgement. AI can help analyse large datasets, identify patterns in investor activity, summarise market information and support disciplined financial planning. Yet behavioural biases cannot be reduced to simple labels, and algorithmic systems can introduce new forms of influence through opacity, personalisation and engagement-oriented design.

The central implication is that responsible AI should support informed agency rather than replace investor judgement. Systems need to communicate uncertainty, protect personal

data, explain recommendations in accessible language and provide routes to human assistance. In India, inclusive design and culturally and linguistically appropriate financial education are especially relevant. Further research should test how AI affects actual decisions over time, which users benefit, and under what conditions technology may amplify existing vulnerabilities. A balanced integration of behavioural insight, technical evaluation and consumer protection can help develop financial tools that are useful, understandable and accountable.

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