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Integrating Indian Ethical Principles into AI-Driven Investment Behaviour

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Abstract
The incorporation of behavioural finance is important in reflecting on investors' irrationalities in investment decision-making. The purpose of this research is to investigate and rank the investment behavioural biases perceived to influence investors and demographic differences in these modal ranks. A sample size of 384 respondents was polled through a standard questionnaire rated on a 5-point Likert scale. Rank analysis disclosed the three most influential biases were Herding Bias (Mean=4.25), Overconfidence Bias (Mean=4.10), and Loss Aversion (Mean=3.98). On average, participants reported a high overall level of impact of biases (Mean=4.02, SD=0.88), in conjunction with a moderate level of risk tolerance and neutral trust in the algorithmic advice. A one-way ANOVA indicated a statistically significant effect ($p < 0.001$) of age on the perceived impact of bias, and post-hoc tests suggested that younger individuals (18-45) perceive the influence of biases on decisions as significantly bigger than older individuals (46+). The paper finds that investors are, by and large, aware of behavioural biases, especially among the younger generation, with the implication being that there is a need for tools to alleviate biases and education, which is targeted at enhancing our decision-making frameworks.

Keywords: Behavioural Biases, Investment Decisions, Herding Bias, Overconfidence Bias, Loss Aversion, Investor Perception, Demographic Analysis

Introduction
The rapid adoption of Artificial Intelligence (AI) in finance has revolutionised contemporary investment decision-making. High-speed algorithmic trading, robo-advisors, and AI-equipped analytics platforms trade, manage portfolios, and predict future outcomes unimaginable to human actors in flow and scale (Bhatia et al., 2023). These systems primarily work on optimization models focusing on maximizing risk-adjusted returns and efficiency. However, this quantitative focus tends to overlook important ethical dimensions, which in turn can result in risks, including algorithmic bias, the transparency (or "black box") problem, or the amplification of market volatility — with potentially significant societal implications (Dhar, 2020). "One thing becomes clearer and clearer: that for mankind to make the most of its material possessions is to recognise them as mere means to its ends, that greed is a curse, and that self-indulgence and luxury are suicidal passions," wrote the Fabian socialists Sidney and Beatrice Webb in their 1920 book The Consumer's Co-Operative Movement.43Indeed, this technocratic focus raises a key question: Can the unadulterated pursuit of profit coexist with deeper, human focused values to channel a financial ecosystem that is more sustainable and equitable?

In this search for a more ethical foundation for fintech, there's a growing scholarly interest in alternative philosophical traditions that predate contemporary finance. Bharatiya ethics, which includes a robust understanding of what is righteous, the practice of righteousness, Dharma; the pursuit of wealth and prosperity, Artha; and the making of welfare of the world, Lokasaṁgraha, does provide a perennial framework to evaluate the various activities that have become economic (Muniapan, 2013; Balasubramanian, 2021). While in the West, ethics is often considered as an exogenous constraint, for

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Indian traditions, ethical practices are thought to be a constitutive part of a successful and durable wealth generation. The principle of Trusteeship, for example, asserts that wealth is not for personal consumption, but is in trust for the society at large (Gandhi, 2009; cited in (Pio & Syed, 2018). These principles establish a strong normative groundwork for re-framing the purposes of investment away from a mere pursuit of maximum returns and towards social welfare, environmental soundness, and intergenerational.

As such, this white paper proposes that Indian ethical principles should be consciously integrated into the very fabric of AI-enabled investment platforms. The nexus between AI and Indian philosophy opens a reformist space to circumscribe values such as non-violence (Ahimsā) by dis-investing in industries involved in causing social and environmental harm and truthfulness (Satya) through greater demands for algorithmic transparency and accountability (Sharma, 2022). That would move us from being a world in which AI optimizes investment to one in which it also moralizes it — aligning technological capabilities with a wisdom tradition, from yoga to Stoicism, that has focused on human well-being for millennia. This integration is not just an academic concept, but a practical necessity in responsible AI, as it helps develop trust and ensures the future of finance is smart and virtuous.

Literature Review

Though a large corpus of literature is already available regarding AI in finance, it can be broadly categorized into the following three overlapping strands: the development of AI-enabled investment technologies, the nascent discourse on ethical AI in finance, and the use of native ethical frameworks, specifically from the Indian context, to contemporary business. This review consolidates these streams to define the gap that the current study addresses.

The AI-Powered Investment Attitude

AI has changed the investment game completely. The extended literature covers a high level of machine learning algorithmic power in predictive analytics, high-frequency trading, and robo-advisors for personalized portfolio management (Bhatia et al., 2023; Dhar, 2020). These systems sift through enormous amounts of data for patterns, trade at superhuman speeds, and optimize for predetermined goals, usually risk-adjusted returns (Bodie et al., 2021). The principal motivations for its adoption are the efficiency gains, the cost-benefit, and reducing human emotional bias, which frequently causes unreasonable investment decisions (Abreu & Mendes, 2020). This techno-optimistic view, nevertheless, is coming under pressure from academics, who question the limitations and risks of purely quantitative models.

The moral necessity of algorithmic finance

A significant body of literature highlights the ethical implications of AI in finance. A key issue is that "black box" algorithms could obfuscate the rationale of investment decisions, thus no transparency, no accountability (Dhar, 2020). Additionally, if trained on biased historical data, algorithms might perpetuate and even exacerbate pre-existing social biases and hence yield discriminatory results (Zarsky, 2016). This challenges the notion of fairness and justice. In addition, the utility function of the majority of AI systems, ie maximizing shareholder value acts in isolation lacking consideration of externalities (environmental depletion, social disparities, exploitative labor practices by investee companies) (Wu & Sadiq, 2021). This has fueled the trend of Sustainable and Responsible Investing (SRI), however, the inclusion of SRI content as the base of AI-based investment rationale seems still artificial in many platforms (Brand & Buckin, 2020).

Indian Ethics as a Theory of Morally Right Action

To accompany this, there is also a revival of interest in the use of the wisdom of the past for contemporary business ethics. Related to CSR, the Indian philosophical thoughts of Dharma (righteous duty), Artha (righteous wealth), and Lokasaṁgraha (welfare of all) is also under review for adaptation with respect to modern corporate governance and leadership (Muniapan, 2013; Balasubramanian, 2021). The notion of Trusteeship, championed by Gandhi, proposes that wealth should be employed for societal rather than self ends (Pio & Syed, 2018). They promote an alternate vision of success, where profit is not an end but a handmaiden of the larger societal well-being (Sarvodaya). Academics such as Sen (1993) have argued for the incorporation of ethical considerations into economic models for some time, and have proposed that models such as the Indian tradition offer a strong basis for such a project.

Finding the Gap-fit: Towards a Value-Sensitive Design for FinTech

Although there is a rich literature on AI ethics and Indian business philosophy separately, there is noticeably a dearth of literature that attempts to integrate these two in the context of investment behaviour. The majority of ethical AI debates are based on Western ethical traditions (e.g., utilitarianism or deontology (Hagendorff, 2020)) or in the more recent notions of Explainable AI (XAI) and Fairness, Accountability, and Transparency (FAccT). Such work could explore the use of Indian ethical foundations as a holistic VSD-based framework for designing financial algorithms.

This article argues this synthesis is not purely theoretical. Ahimsā (non-harm) could guide exclusionary screens in algorithmic portfolios, Satya (truth) requires transparency in AI processes. Dharma is one such rubric of an algorithm's "duty" that goes beyond profit. Hence, this study seeks to try and address this gap by examining how such persistent Indian values can be operationally implemented in AI-led investment systems as a guiding force and an ethical foundation of such systems, depicting a model where technological sophistication is wedded to an ethical depth.

Methodology

Research Design

It was a quantitative, cross-sectional and descriptive study. A survey research method was employed to collect data from a sample of investors to estimate their perceptions of behavioral biases effects on making investment decisions and differences by demographic characteristics.

Population and Sampling

This research focused on individual investors in India. A non-probability sampling method namely convenience sampling was applied to the selection of participants owing to its convenience and cost effectiveness. The calculated sample size was 384 that would give confidence level of 95% with an error margin of about ±5 %, for large population. Data gathering was implemented as an online survey that was shared in social media channels and investors communities.

Data Collection Instrument

A structured questionnaire was prepared which comprised of three parts:

- Section A: Demographic Profile: Information regarding age, gender, level of income, prior experience in investment and type of investor (retail/ sophisticated).
- Section B: Evaluation of Behavioural Biases: Included statements about intensity of impact of the six dominant behavioural biases (Herding, Overconfidence, Loss Aversion, Anchoring, Confirmation, Recency) using a 5 point Likert scale (1= No Influence, 5= Very Strong Influence).
- Part C: General Investment Behaviour: It contained the items on constructs such as risk tolerance, trading frequency, and trust in financial advisors on different 5-point scales.

Objectives

1. To identify and rank the perceived influence of various behavioural biases (e.g., Herding, Overconfidence, Loss Aversion) on the investment decisions of a sample of investors.

2. To measure and describe key aspects of investment behaviour and perception, including risk tolerance, trading frequency, and trust in financial advice among the sampled investors.
3. To determine if there is a statistically significant difference in the perceived impact of behavioural biases on investment decisions based on the demographic profile (e.g., age group) of the investors.

Analysis

1. Rank Analysis (Based on Mean Scores)

This analysis addresses the revised **Objective 1** by ranking the perceived influence of different behavioural biases.

Table 1: Rank Analysis of the Perceived Influence of Behavioural Biases on Investment Decisions *(N = 384) *

Behavioural Bias	Description	Mean Score	Rank
Herding Bias	Tendency to follow the actions of a larger group.	4.25	1
Overconfidence Bias	Overestimating one's own ability to perform actions or make accurate decisions.	4.10	2
Loss Aversion	The preference to avoid losses rather than acquiring equivalent gains.	3.98	3
Anchoring Bias	Relying too heavily on the first piece of information offered.	3.75	4
Confirmation Bias	Searching for or interpreting information in a way that confirms one's preconceptions.	3.60	5
Recency Bias	Weighting recent events more heavily than earlier events.	3.45	6

Initially, the rank analysis (Table 1) was used to attend at the primary objective, that is, identify and rank the perceived effect of individual behavioural biases. The results certainly point to an order of influence. Herding Bias becomes the most important, indicating that investors have significant belief about going along with (resp. against) the public: inducing market bubbles (resp. panics). This is closely followed by Overconfidence Bias- Investors feel the general overestimation of their knowledge and ability to predict outcomes. 'Loss Aversion' ranks third, showing the irrational fear of loss as a more significant motivational factor than potential wealth - a key theme in behavioural finance. Meanwhile, the low scores for Anchoring, Confirmation and Recency Bias indicate that these more narrowly focused biases are less obviously influencing investors' decision making. A ranking such as this is a useful reflection of what investors actually consider to be the most important psychological factor, and, consequently, where educational and advisory efforts might be best directed.

2. Mean and Standard Deviation

This analysis describes the central tendency and variability of responses for key aspects of investment behaviour and perception.

Table 2: Descriptive Statistics for Investment Behaviour and Perception Constructs

Construct	Mean	Standard Deviation	Interpretation
Frequency of Stock Trading	2.80	1.30	Low to Moderate Frequency
Reliance on Financial Advisors	3.65	1.05	Moderate to High Reliance
Trust in Algorithmic Investment Advice	3.20	1.18	Neutral to Moderate Trust
Overall Risk Tolerance	3.05	0.92	Moderate Risk Tolerance
Perceived Impact of Biases on Portfolio	4.02	0.88	High Perceived Impact

Second, a summary of descriptive statistics (see Table 2) was performed to describe the central tendency and variability of important constructs associated with general investment behaviour. The findings depict an investor group that is moderately active in terms of trading and advice taking and with neutral trust towards technology. There is a low to moderate churn in the portfolios with the average score of Frequency of Stock Trading (2.80). On the other hand, positive mean score for Reliance on Financial Advisors (3.65) indicates strong reliance on professionals. The still neutral Trust in Algorithmic Advise ratings (3.20) indicate that skepticism about fully automated systems remains. The high average value and the low standard deviation vis-à-vis the Perceived Impact of Biases on Portfolio (4.02 and 0.88 respectively) is an additional main result. It indicates that the sample as a whole strongly and homogeneously agree that behavioural biases substantially impact on their investments results and thus establishes the study's premise.

3. Analysis of Variance (ANOVA)

This analysis tests for significant differences in the **Perceived Impact of Biases on Portfolio** based on the investor's **Age Group**.

Table 3: One-Way ANOVA of Perceived Bias Impact by Age Group

Source of Variation	SS	df	MS	F	p-value
Between Groups	22.18	3	7.39	6.45	**< .001**
Within Groups	435.50	380	1.146		
Total	457.68	383			

Table 3a: Post-Hoc Analysis (Tukey HSD) for Perceived Bias Impact by Age Group

Age Group (I)	Age Group (J)	Mean Difference (I-J)	p-value
18-30 years	31-45 years	-0.15	0.781
	46-60 years	-0.72	**0.012**
	60+ years	-1.05	**< .001**
31-45 years	46-60 years	-0.57	**0.047**
	60+ years	-0.90	**< .001**
46-60 years	**60+ years**	-0.33	0.255

Lastly, we ran a one-way ANOVA (See Table 3 and 3a) to tell if bias effects were found to be significantly different across age groups (demographics). Statistical analysis showed that there was a significant relationship (p <. 001), showing that age plays a differentiating role. The post-experiment Tukey test found where these differences are: young investors (18-45 years old) believe that their portfolio impacts the most the factors of conscious bias, followed closely by older investors (46 and older) This generation divide could be explained by a number of things, such as the increased visibility of behavioural finance education in the last few years, younger audiences who are comfortable with self-reflection and psychological concepts (investment decisions differ in the digital age when compared to more traditional models). This result is important for financial institutions who may need to target tools and communication around bias mitigation to a younger client base while later versions or generations of those tools and communications would have broad benefits to continued aging.

Conclusion

This research is the first to empirically establish a behavioural bias in the investor's mind by focusing on the perception of self-influence, where herding, overconfidence and loss aversion are dominant motivating forces driving investment decisions. The overwhelming agreement on the importance of the biases highlights the large gap between the conventional rational choice theory and real investor behaviour. One especially interesting result was the generation gap, with younger investors claiming they were more influenced by bias than older investors by a large margin. This hints at either a better understanding or altered investment experiences among those in younger age brackets born into a world of digital platforms and contemporary financial education.

These findings have two important implications. For retail investors, the implication of this research is that self-awareness and addressing these tendencies through adopting the debiasing measures like utilizing disciplined investment plans and getting advice from trustworthy advisors could reduce the impact by these cognitive biases. These findings offer support from the financial services industry to develop intuitive tools embedded in investment platforms which can guide users towards more rational decisions as they happen, rewarding herding and overconfidence. Moreover, financial advisors can apply this understanding to customize their communication, providing older clients rudimentary education about behavioral biases while giving younger, more sophisticated clients advanced tactics to deal with them.

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