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# Behavioral Biases in Investment Decision-Making

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**Abstract:** Investment decisions are not always logical or rational. When making financial decisions in the real world, people are guided by their emotions and personal history, and they take mental shortcuts that don't always lead to the right decisions. These are influences known as behavioural biases. This review article considers the most relevant biases impacting investor decision-making. It discusses ideas from behavioural finance, a discipline that integrates psychology and economics to explain why people sometimes make bad decisions in financial markets. The paper also describes how these biases affect stock markets, individual investors, and portfolio managers. It draws on theories such as the Prospect Theory of Kahneman and Tversky, as well as several empirical studies from both advanced and emerging markets. The paper concludes by suggesting possible mitigating actions for the biases.

***Keywords:*** Behavioural biases, investment decision-making, behavioural finance, cognitive biases, prospect theory, overconfidence, herding, loss aversion.

## 1. Introduction: Behavioural Biases in Investment Decision-Making

When people think of investing money, they seem to have an image of these investors as rational, who read all of the relevant materials and then make decisions that maximise their financial returns. This concept is at the core of classic finance principles, such as the Efficient Market Hypothesis (EMH), which states that asset prices always incorporate all available information. Yet the real world answers differently. A large number of investors make terrible decisions not because they don't have enough information, but because they allow their thinking to become skewed by psychological pressures. They may sell losing positions too quickly, buy too many stocks, ride too long on losing stocks, buy and sell according to the wind, or think too much of their own talents. Such behaviour is a form of bias in investor psychology and has a great impact on investment decisions. The psychological factors responsible for this are studied in behavioural finance. It draws on psychology and economics to understand why investors sometimes behave irrationally. Beginning in the 1980s, scholars such as Daniel Kahneman and Amos Tversky demonstrated in a series of experiments that individuals routinely break the rules of logical decision-making in systematic ways. In recent years, there has been a growing recognition of the need to understand behavioural biases. Periods of stock market crashes, asset bubbles, and poor outcomes for individual investors can be largely attributed to the influence of pervasive behavioural biases among those investors. They include, for example, the dot-com bubble in the late 1990s, or the 2008 financial crisis, both of which were associated in part with herd behaviour and overconfidence [1][7][18].

## 2 Theoretical Background

### 2.1 Traditional Finance vs. Behavioural Finance

Conventional finance rests on the premise that investors are fully rational. About the EMH The EMH, formulated in the 1960s by Eugene Fama, states that the most up-to-date information is already incorporated into the stock's price. Therefore, consistently beating the market is not feasible, since prices always reflect fair value. But the tide began to turn for that theory when economists realised that markets do occasionally behave in ways that can't be explained by rational models. For instance, stock prices occasionally rise or fall dramatically for no apparent reason. Investors tend to sell winning stocks too soon and hold on to losing stocks for far too long. These trends are indicative of psychological influences [141][143].

Behavioural finance is said to have been born out of the need to fill this gap. It doesn't view investors as perfectly rational. It merely recognises that people are subject to cognitive biases, emotional influencers, and social pressures that impact their financial decisions.

### 2.2 Prospect Theory

Prospect Theory is by far the most dominant theory in behavioural finance, which was proposed by Daniel Kahneman and his collaborator Amos Tversky in 1979. This theory revolutionised the study of decision-making under uncertainty among economists. Prospect Theory suggests that we do not perceive outcomes in terms of "absolute wealth". Instead, they judge gains and losses from a reference point, typically what they own or the purchase price of an asset. The theory has two core elements: • Loss Aversion: The pain of losing is about twice as strong as the pleasure of gaining. Take the case of losing Rs. 1,000, which is worse than the feeling of gaining Rs. 1,000 comforts. • Diminishing Sensitivity: Just as people are less sensitive to small changes far away from a reference point, people also become less sensitive to changes as they get larger. The difference in the feeling of gaining Rs. 100 and Rs. 200 is more than that between Rs. 1,000 and Rs. 1,100. Prospect Theory accounts for many real-life investment behaviours, including why investors hold on to losing stock (to avoid realising a loss) and why they sell their winning stock too quickly (to realise a gain).

### 2.3 Bounded Rationality

Yet another key notion is bounded rationality, introduced by Herbert Simon. Simon contended that people have limited cognitive capacity and the availability of perfect information. Rather, they make decisions based on simplified mental representations of the world and on rules of thumb, known as heuristics. Heuristics can be useful shortcuts, but they can also lead to systematic errors in judgment; these errors are the cognitive biases that we will consider in the next section.

### 2.4 Noise Trader Theory

The theory that is most closely related is the De Long et al. (1990) Noise Trader Theory, which argues that irrational investors (referred to as 'noise traders') can have a significant impact on asset prices. Rational investors base their trades on fundamental information, whereas noise traders trade based on rumours, emotions or short-term trends. Certainly, the distortion in prices caused by noise traders is dangerous to arbitrage, so even rational traders may not be able to completely correct it. This helps to explain how markets can remain irrational for so long [12][29][69].

## 3. Major Behavioural Biases in Investment Decision-Making

### 3.1 Overconfidence Bias

Overconfidence is one of the most popular and best-documented behavioural biases. It is a description of investor psychology in which investors overplay their knowledge of the market, and they think they know more than they actually do. Confident investors think they are above-average — what has been colloquially termed the "better-than-average effect". Overconfidence in investing causes investors to trade too much. Confident investors who think they have an edge and can spot things others can't trade. Nevertheless, Barber and Odean (2000) found that those investors who traded most suffered the greatest reduction in return due to transaction costs and bad timing. Overconfidence also causes under-diversification. Overconfident investors also tend to put all their eggs in a few baskets; that is, they hold a few stocks rather than diversifying across many. This increases the chance of significant loss. Research by Glaser and Weber (2007) demonstrated that investors overestimate the accuracy of their own predictions. Not even the professional fund managers — overconfidence is rife, as multiple studies have shown that fund managers tend to build portfolios that underperform the market.

### 3.2 Loss Aversion

The typical effect of loss aversion is the 'disposition effect', the proclivity to realise gains excessively quickly and to hold on to losing assets for excessively long. Investors sell winners because they want to lock in the gain (and perhaps save themselves from the prospect of losing it).

It also leads to subpar portfolio performance. Loss aversion also causes further caution in market declines for investors. Loss-averse investors will also frequently panic and sell at the bottom of a downturn in markets, thereby locking in their

losses rather than holding to recover. As described in Prospect Theory, loss aversion is the idea that we fear losses more than we enjoy equivalent gains. This bias strongly influences investment decisions. Investors who are loss-averse will avoid taking any action that might lead to a loss, even when the expected value of the outcome is positive. “Glass half full / half empty? Impact of loss aversion as per the figure. 1


Figure 1: Loss Aversion

### 3.3 Herding Behaviour

Herding is the tendency of investors to mimic each other's behaviour—purchasing and selling the same assets, rather than conducting their own analysis. This behaviour can be described by two herding models: the informational herding (people believe that others have better information) and the reputational herding (fund managers imitating others to avoid standing out). Herding is known for being an important determinant of asset bubbles and market crashes. With the same asset being spruced across investors due to a perception that everyone else is buying it, the asset’s price is bid up beyond its intrinsic value. And when sentiment turns, and the masses are selling, prices can collapse double-quick. The dot-com bubble (1999-2000) is a very good example of herding. Investors were bidding up technology stocks not because they had all done rigorous analysis, but because everyone they spoke to was doing the same thing and making money. When the bubble burst, a lot of investors lost heavily[41][89][99]. Bikhchandani and Sharma (2001) reviewed the literature on herding and concluded that there is conclusive evidence of herding in both developed and emerging stock markets. They further observed that herding is widespread in emerging markets such as India, China and Brazil, and information is less reliable, and investors tend to follow other investors.

### 3.4. Anchoring Bias:

Anchoring is the bias of relying too heavily on the first piece of information when making decisions. In investing, it frequently means investors fixate on a particular number, such as the original purchase price of a stock, and they treat that number as an anchor for all their future choices. Take, for example, when an investor buys a stock for Rs. 500 and has a mental target of Rs. 600 as the 'right' selling price, without taking into account that the stock's fundamentals may have altered drastically. They are anchored to the purchase price and refuse to lift their estimates when faced with further news. Anchoring can also influence how investors assess analyst projections. If a broker cuts a stock’s target from Rs. 1,000 to Rs. 800, investors may still feel good about the stock because they are anchored to the higher price, even if Rs. 800 is too high. Tversky and Kahneman (1974) were the first to demonstrate anchoring in their well-known experiment, which involved participants estimating percentages after spinning a wheel landing either on 10 or 65. Participants’ estimates were highly affected by the number on the wheel, showing that even irrelevant anchors can influence decision-making [2][15][37].

### 3.5 Confirmation Bias

Confirmation bias is the human tendency to search for, interpret, favour, and recall information in a way that affirms one's existing beliefs or hypotheses. Investors who have confirmation bias seek out news and information that supports their existing theses, and they either ignore or discount news that challenges them. For example, a bullish investor on a certain stock might ignore negative reports while focusing on positive developments of the company. This is why you see people irrationally holding on to a bad investment for an extended period of time as they continue to come up with new reasons to explain away why they were wrong. Confirmation bias is particularly pernicious because it can give us a misleading sense of confidence. Investors believe they have done their homework when they discovered supporting evidence for their point of view, but that really just means they haven't critically challenged their own thesis by giving serious consideration to the opposing evidence. Lord, Ross, and Lepper (1979) studied confirmation bias in the context of capital punishment using an experimental design in which respondents who favoured and opposed capital punishment evaluated the same set of studies; they found that respondents considered studies that supported their pre-existing view as more persuasive, irrespective of the rigour of the research [4][19][85].

### 3.6 Availability Bias

Availability bias is when individuals base their decisions on information that they can easily retrieve from their memory instead of from complete or objective data. In investing, this can translate into recent or headline-grabbing news having an outsized impact on decisions, as per Figure 2

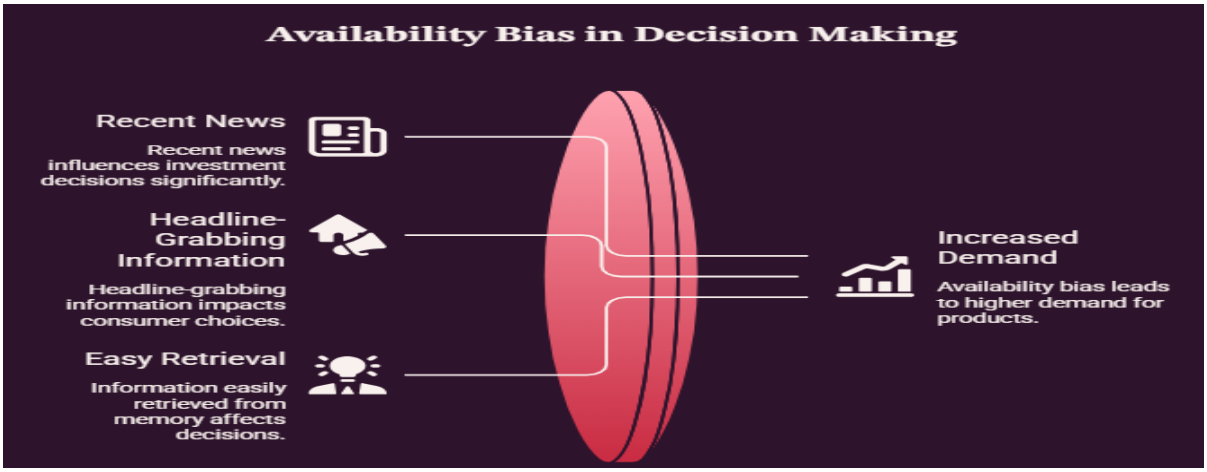


Figure 2: Availability Bias In Decision Making

For example, in the wake of a large stock market crash, investors may overestimate the chance of another crash occurring in the near term simply because the event is so vivid and fresh in their minds. On the flip side, during a prolonged bull market, investors might be underestimating risk because no crash has occurred in a while. Availability bias causes investors to also overweigh the information that they just keep on hearing, like the news on big firms that already have a crown of popularity over them, and underweigh the information of lesser-known, but possibly better, investment firms. This can create overexposure to well-known companies and underexposure to smaller, less-covered opportunities [115][121][110].

### 3.7 Mental Accounting

Mental accounting, a term coined by Richard Thaler, describes the phenomenon in which people divide their money into separate mental accounts based on specific categories and then use different criteria when evaluating expenditures from the various accounts. For instance, an investor may be a big risk taker with his poker winnings ("house money"), but be very conservative with his salary, despite the fact that "money's money," no matter where it comes from. In the same way, investors may value dividend income differently from capital gains income, even though they should regard both as increases to their wealth. Mental accounting can also cause bad portfolio decisions. For instance, investors may segregate their portfolio into a 'safe' pool (low-yield bonds) and a 'risky' pool (speculative equities) instead of looking at their portfolio on an aggregate basis. This can create an overall portfolio that does not reflect the real risk preferences.

### 3.8 Representativeness Bias

Representativeness bias refers to a phenomenon in which investors estimate the probability of an event occurring based on how similar it is to a stereotype (or experience), rather than on the real, statistical probabilities. This can result in inaccurate forecasting of what future performance will be. A classic illustration: the "hot hand" fallacy — the assumption that a fund manager or stock that has done well recently will keep doing well. Instead, historical performance is generally a bad indicator of future results. However, investors tend to mistake a winning streak for skill rather than luck, and so they chase past performance [9][117].

### 3.9 Status Quo Bias

Status quo bias is an emotional bias where the existing baseline or status quo is taken as a reference point, and any change from that baseline is perceived as a loss. Biased investors are also unwilling to change their portfolio, even when doing so would obviously be in their best interest. They cling to their old investments just as a drug addict clings to his drug of choice -- doing nothing is safer, doing nothing is more comfortable. Such bias may hinder an investor from rebalancing their portfolio, from moving into better investment options or from cutting their losses. Samuelson and Zeckhauser (1988) illustrated this effect in the context of investors, showing that people tend to stick with default options in investments, further demonstrating the power of inertia in financial decisions[40][139].

## 4. Impact of Behavioural Biases on Markets and Investors

### 4.1 Impact on Individual Investors

Behavioural biases in a retail investor lead to detrimental effects on investment returns, risk-taking or risk-avoiding. Individual investors tend to underperform the market, as shown in various studies. One important driver of this is overconfidence-induced excessive trading, which entails high transaction costs. The disposition effect—too-early sale of winners and too-late sale of losers—also diminishes returns. Odean's (1998) research found that the individual investors' sold stocks outperformed their held stocks by approximately 3.4% in the year following sale, suggesting that investors may be selling the wrong stocks. Bias towards losses. Many individual investors lose out on returns because they are too cautious or are nervous about investing, as per figure 3 [102][104][110].

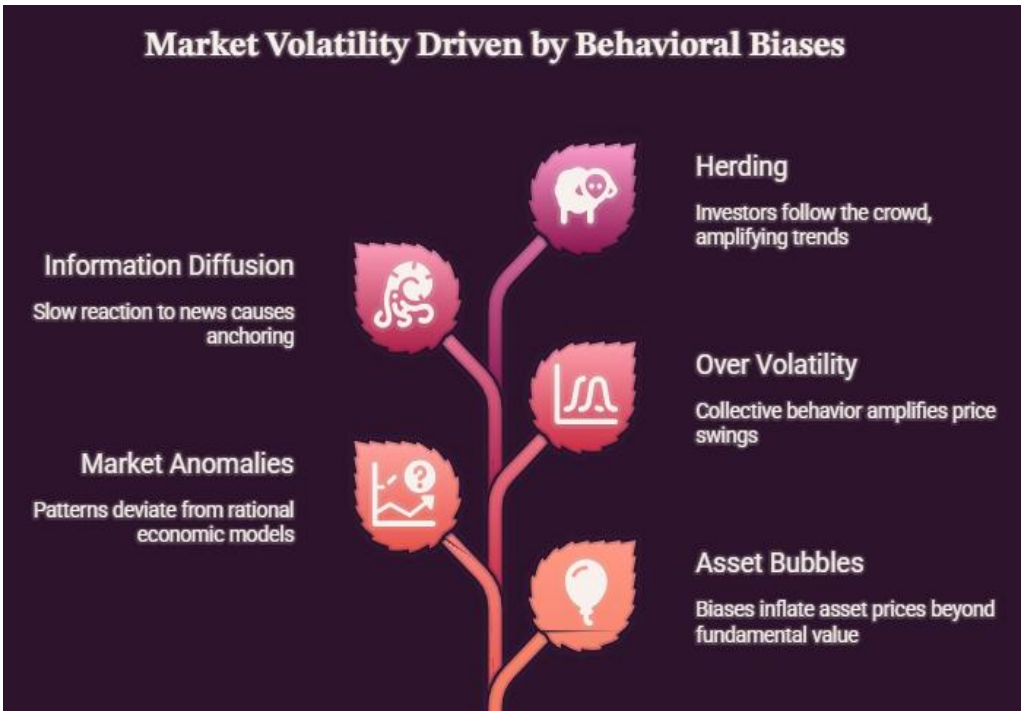


Figure 3- Market Volatility Driven Y Behavioural Biases

### 4.2 Impact on Financial Markets

At the market aggregate level, behavioural biases bring about such phenomena as asset bubbles, market anomalies, and overvolatility. These biases can sometimes be shared by a large number of investors, leading to collective behaviour that can drive asset prices away from their fundamental value. Market anomalies — which are patterns in stock return that cannot be justified by rational models — are frequently ascribed to behavioural biases [140]. The January effect (stocks tend to rise in January) can be explained by tax-loss selling in December, followed by repurchasing in January – a form of behaviour associated with loss aversion and mental accounting.

### 4.3 Summary Table of Biases and Their Effects

**Table 1: Biases and Their Effects**

| Behavioral Bias | Main Cause | Investment Behavior | Market Effect |
|---|---|---|---|
| Overconfidence | Overestimation of skill | Excessive trading, under-diversification | Increased market volatility |
| Loss Aversion | Fear of losses > joy of gains | Disposition effect, panic selling | Downward price spirals |
| Herding | Following the crowd | Buying/selling with the majority | Bubbles and crashes |
| Anchoring | Fixation on the reference price | Ignoring new information | Price stickiness |
| Confirmation Bias | Seeking validating info | Holding bad investments | Delayed price correction |
| Availability Bias | Over-relying on recent events | Overweighting recent crashes/booms | Excess volatility |
| Mental Accounting | Categorizing money | Sub-optimal portfolio allocation | Market inefficiencies |
| Representativeness | Stereotyping outcomes | Chasing past performance | Performance persistence myths |
| Status Quo Bias | Preference for inaction | Failure to rebalance the portfolio | Slow market adjustment |

### 4.4 Impact on Institutional Investors and Fund Managers

Institutional investors and fund managers are biased , too. Evidence of herding among mutual fund managers has been documented in several studies — they appear to trade in the same stocks at the same time, generating correlated trading patterns, which have the potential to magnify market movements. Overconfidence is prevalent among professionals as well. Many fund managers have an illusion of skill and think they can beat the market on a consistent basis, despite the fact that most actively-managed funds underperform their benchmark index over long periods, especially after fees. Reputational concerns can lead to irrational behaviour. Fund managers can herd because straying from the consensus view on the market is risky — if they make a contrarian bet and lose, they will get fired, whereas if they follow the herd and lose, they can at least say that "everyone else lost too."

## 5. Strategies to Reduce Behavioural Biases

### 5.1 Education and Awareness

The first step in correcting behavioural biases is simply understanding that they exist. Financial literacy and investment education may enable investors to identify their own biases and to be better informed regarding how these biases could impact their decisions. Research has shown that investors who are educated about the disposition effect, for example, are less likely to succumb to it. A number of universities and financial firms now provide behavioural finance courses that educate investors on cognitive biases and ways to mitigate their effects. Regulators such as SEBI in India and the SEC in the U.S. have also started integrating behavioural finance concepts in investor awareness programs [11][115][150].

### 5.2 Setting Rules and Pre-Commitments

A rule-based investing approach is biased in its own way, but by deciding on your investment strategy in advance—prior to having your emotions hijacked—you stand a much better chance of reducing bias. For example, as an investor, you may decide in advance that you will sell a stock if it drops 10% from what you paid for it (stop-loss rule), or that you will rebalance your holdings to your desired asset allocation twice a year. Such investment decisions are better made in a non-emotional state of mind and when an investor is less likely to be influenced to change them on the fly (based on prevailing market sentiment). This method is consistent with research on self-control and pre-commitment schemes (Thaler and Benartzi, 2004) [118][97].

### 5.3 Diversification and Passive Investing

Diversification is strong medicine for overconfidence and availability bias. When you diversify your investment portfolio by including different asset classes, industry sectors or geographic regions, you are protecting yourself against the risk of overexposure to a small handful of familiar or popular investments. Passive investing — buying index funds that follow a market benchmark — is another way. Because they are not dependent on picking individual stocks, index funds are not subject to many of the biases that active investing entails, like overconfidence, confirmation bias and anchoring. Studies consistently find that the majority of active managers underperform their benchmark index over time, and one key explanation is the behavioural biases of these fund managers [132][120].

### 5.4 Using Checklists and Systematic Processes

Professional investors and analysts can mitigate bias through the use of structured checklists and processes for executing investment decisions. To mitigate the effect of confirmation bias (and overconfidence), investment firms can force analysts to weigh positive and negative evidence, challenge their assumptions, and act as "devil's advocate." Daniel Kahneman recommends what he calls a 'pre-mortem' — the act of imagining that a decision you've yet to make has already failed and thinking about why before you make it. This compels investors to recognise potential downsides, which they might have ignored on the grounds of optimism or confirmation biases [3][78][79].

### 5.5 Nudges and Choice Architecture

Behavioural economists have discovered that the framing of choices can influence decisions. 'Nudges' are slight design tweaks that steer people toward better behaviour without limiting choice. Like enrolling employees in pension plans automatically (and giving them the option to opt out), which greatly increases participation, as demonstrated in the work on choice architecture by Thaler and Sunstein. Nudges can also be applied by financial product designers and employers to help investors make better decisions [111][116][130].

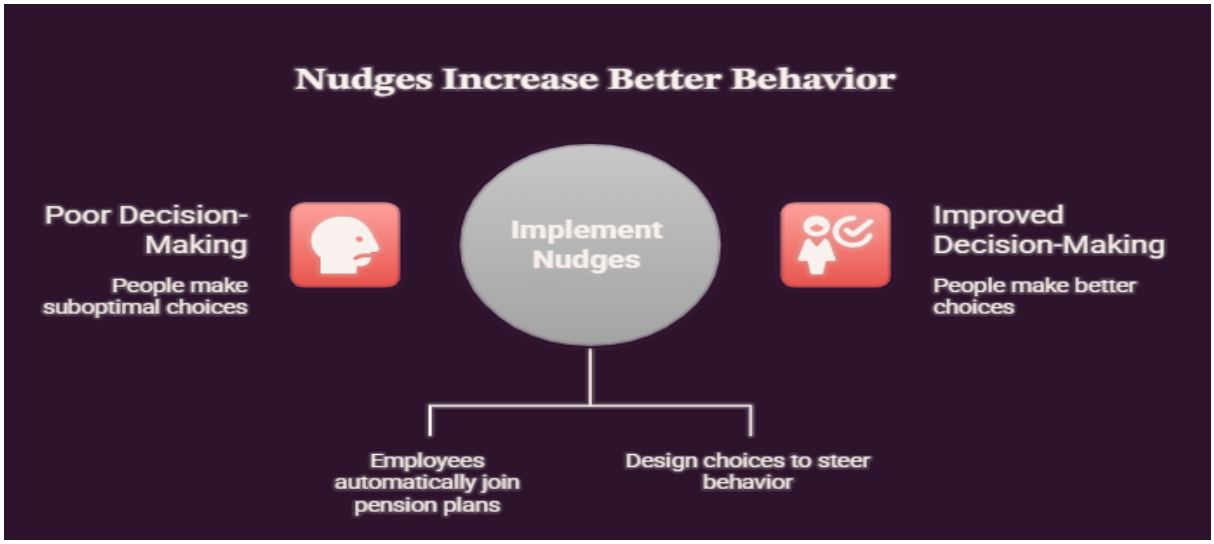


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Figure 4: nudges increase better behaviour

Simply presenting investment choices in a way that promotes diversification, or defaulting retirement saving contributions to higher levels, can have a material effect on long-term investment results [119][129].

### 5.6 Seeking Independent Advice

An individual investor can be enabled to make more rational decisions by a financial advisor who is educated in the identification and mitigation of behavioural biases. A good advisor is a 'behavioural coach,' constantly reminding investors of their long-term goals when short-term market action tempts them to make emotional decisions. But it should be noted that advisors themselves are not impervious to biases. Studies indicate that financial advisors can also be subject to herding and overconfidence. The holy grail is an advisor who is both technically proficient and trained in behavioural finance [111][136][134].

## 6. Review of Key Studies

The investigation of behavioural biases in investing has blossomed into a generous field of enquiry. Some (but not necessarily all) of the most relevant related work is: The origin of behavioural finance: Prospect theory, Kahneman and Tversky( 1979) established the basis of behavioural finance with Prospect Theory. Their work demonstrated that individuals assess outcomes with respect to a reference point, and they are more responsive to losses than to gains. Kahneman (with Tversky) 1992 is among the most cited papers in economics and won Kahneman the Nobel in 2002. Shefrin and Statman (1985) were the first to identify the disposition effect, using data from a large brokerage firm. They uncovered pattern-related evidence that investors hang on to losers and dump winners — a behaviour consistent with loss aversion and mental accounting. De Bondt and Thaler (1985) established that stocks that had performed 'badly' (well) in the prior three to five years tend to outperform (underperform) stocks that had performed well (badly) during the same period. This 'reversal effect'is inconsistent with the concept of an efficient market, and is interpretable as an overreaction originating from representativeness bias. Barber and Odean (2000) studied the transactions of more than 60,000 households and discovered that the most active traders earn average net returns 6.5 percentage points per year lower than the least active traders. They attributed this to overconfidence[113][125][145].

Odean (1998) showed that individual investors systematically sell their winning investments and hold their losing investments — the disposition effect — and that this behaviour reduces their returns.

Bikhchandani and Sharma (2001) reviewed the herding in financial markets and distinguished two types: intentional herding (in which investors deliberately follow others) and spurious herding (in which investors actually react to the same information and thus act in a similar manner). Urlencoded. You are encouraged to share this article with your friends and colleagues. Thaler (1985) introduced the notion of mental accounting and demonstrated how this results in behaviour that is inconsistent with economic theory, such as treating "windfall" money differently from money earned with effort. Jain and Sehgal (2019) examined behavioural biases of Indian retail investors and observed evidence of strong overconfidence, herding and disposition effect in the Indian stock market. Their results also implied that these biases are not peculiar to Western investors only but exist globally [132][144][157][158].

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## 7. Conclusion

This article has reviewed the most important behavioural biases investors exhibit. 2 We have learned that investors aren't the fully rational organisms that traditional finance Theorists would like to believe them to be. Rather, they are subject to a host of psychological influences such as overconfidence, loss aversion, herding, anchoring, confirmation bias, availability bias, mental accounting, representativeness, and status quo bias. These biases aren't occurring haphazardly or due to some unpredictable factors — they are systematic and stable across investors, markets, and cultures. They influence not only individual retail investors but also professional fund managers and institutional investors. At the level of the market as a whole, they help explain such phenomena as asset bubbles, market crashes, and long-lived market anomalies. Everyone involved in finance needs to understand behavioural bias. For retail investors, it can help them better identify their own blunders and make wiser long-term decisions. For financial advisors, it offers tools to help clients stay on track through stressful market environments. To policymakers and regulators, it informs how financial systems and products can be designed so as to better guide investors away from common traps.

Behavioural finance has evolved considerably since Kahneman and Tversky developed Prospect Theory in 1979. It has transitioned from the periphery of academic research to the core of financial theory and practice. Now, insights from behaviour are being applied to create better pension plans, to refine financial regulation, and to design investment products that capitalise on human psychology instead of fighting it. That said, there is a lot to be done. Future research may also investigate how behavioural biases change in a different technological era, e.g. with the introduction of artificial intelligence and robo-advisors that can aid investors in the decision-making process, and how these biases interrelate to form more complex patterns of investor behaviour. To conclude, behavioural biases are intrinsic to investment decisions. Not dealing with them is what causes bad financial results for individuals and market turmoil. Recognising and mitigating them — with education, improved processes, and intelligent system design — can result in more informed decision making and greater financial well-being for all.

**References**


[1] Garg, P., Dixit, A., &Sethi, P. (2019). Wireless sensor networks: an insight review. *International Journal of Advanced Science and Technology*, *28*(15), 612-627.

[2] Sharma, N., & Garg, P. (2022). Ant colony-based optimisation model for QoS-Based task scheduling in cloud computing environment. *Measurement: Sensors*, 100531.

[3] Kumar, P., Kumar, R., & Garg, P. (2020). Hybrid Crowd Cloud Routing Protocol For Wireless Sensor Networks. *International Journal of Advanced Science and Technology*, *29*, 766-775.

[4] Raj, G., Verma, A., Dalal, P., Shukla, A. K., & Garg, P. (2023). Performance Comparison of Several LPWAN Technologies for Energy-Constrained IoT Network. *International Journal of Intelligent Systems and Applications in Engineering*, *11*(1s), 150-158.

[5] Garg, P., Sharma, N., & Shukla, B. (2023). Predicting the Risk of Cardiovascular Diseases using Machine Learning Techniques. *International Journal of Intelligent Systems and Applications in Engineering*, *11*(2s), 165-173.

[6] Patil, S. C., Mane, D. A., Singh, M., Garg, P., Desai, A. B., &Rawat, D. (2024). Parkinson's Disease Progression Prediction Using Longitudinal Imaging Data and Grey Wolf Optimiser-Based Feature Selection. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(3s), 441-451.

[7] Gudur, A., Pati, P., Garg, P., & Sharma, N. (2024). Radiomics Feature Selection for Lung Cancer Subtyping and Prognosis Prediction: A Comparative Study of Ant Colony Optimisation and Simulated Annealing. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(3s), 553-565.

[8] Khan, A. (2024). Optimisation Methods Based on Soft Computing for Improving Power System Stability. *J. Electrical Systems*, *20*(6s), 1051-1058.

[9] Sharma, K. K., Verma, P. K., & Garg, P. (2024). IoT-Enabled Energy Management Systems For Sustainable Energy Storage: Design, Optimisation, And Future Directions. *Frontiers in Health Informatics*, *13*(8).

[10] Gupta, S., Yadav, N., Singh, K., & Garg, P. (2025). APPLICATIONS OF SIMULATIONS AND QUEUING THEORY IN A SUPERMARKET *Reliability: Theory & Applications*, *20*(1 (82)), 135-140.

[11] Beniwal, S., Garg, P., Rajpal, R., Sharma, N., & Mittal, H. K. (2025). Fusion of Opportunistic Networks with Machine Learning: Present and Future. *Metallurgical and Materials Engineering*, *31*(1), 311-324.

[12] Garg, P. (2025). Explainable AI & Model Interpretability in Healthcare: Challenges & Future Directions. *EKSPLORIUM-BULETIN PUSAT TEKNOLOGI BAHAN GALIAN NUKLIR*, *46*(1), 104-133.

[13] Rani, P. (2025). From Data to Diagnosis: Unleashing AI and 6G in Modern Medicine. *EKSPLORIUM-BULETIN PUSAT TEKNOLOGI BAHAN GALIAN NUKLIR*, *46*(1), 69-103.

[14] Dixit, A., Garg, P., Sethi, P., & Singh, Y. (2020, April). TVCCCS: Television Viewer's Channel Cost Calculation System on Per-Second Usage. In *IOP Conference Series: Materials Science and Engineering* (Vol. 804, No. 1, p. 012046). IOP Publishing.

[15] Sethi, P., Garg, P., Dixit, A., & Singh, Y. (2020, April). Smart number cruncher–a voice-based calculator. In *IOP Conference Series: Materials Science and Engineering* (Vol. 804, No. 1, p. 012041). IOP Publishing.

[16] S. Rai, V. Choubey, Suryansh and P. Garg, "A Systematic Review of Encryption and Keylogging for Computer System Security," *2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT)*, 2022, pp. 157-163, doi: 10.1109/CCiCT56684.2022.00039.

[17] L. Saraswat, L. Mohanty, P. Garg and S. Lamba, "Plant Disease Identification Using Plant Images," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 79-82, doi: 10.1109/CCiCT56684.2022.00026.

[18] L. Mohanty, L. Saraswat, P. Garg and S. Lamba, "Recommender Systems in E-Commerce," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 114-119, doi: 10.1109/CCiCT56684.2022.00032.

[19] C. Maggo and P. Garg, "From linguistic features to their extractions: Understanding the semantics of a concept," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 427-431, doi: 10.1109/CCiCT56684.2022.00082.

[20] N. Puri, P. Saggar, A. Kaur and P. Garg, "Application of ensemble Machine Learning models for phishing detection on web networks," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 296-303, doi: 10.1109/CCiCT56684.2022.00062.

[21] R. Sharma, S. Gupta and P. Garg, "Model for Predicting Cardiac Health using Deep Learning Classifier," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 25-30, doi: 10.1109/CCiCT56684.2022.00017.

[22] Varshney, S. Lamba and P. Garg, "A Comprehensive Survey on Event Analysis Using Deep Learning," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 146-150, doi: 10.1109/CCiCT56684.2022.00037.

[23] Dixit, A., Sethi, P., Garg, P., &Pruthi, J. (2022, December). Speech Difficulties and Clarification: A Systematic Review. In *2022, the 11th International Conference on System Modelling & Advancement in Research Trends (SMART)* (pp. 52-56). IEEE.

[24] Garg, P., Dixit, A., Sethi, P., &Pruthi, J. (2023, December). Strengthening Smart City with Opportunistic Networks: An Insight. In the *2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech)* (pp. 700-707). IEEE.

[25] Rana, S., Chaudhary, R., Gupta, M., & Garg, P. (2023, December). Exploring Different Techniques for Emotion Detection Through Face Recognition. In *2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech)* (pp. 779-786). IEEE.

[26] Mittal, K., Srivastava, K., Gupta, M., & Garg, P. (2023, December). Exploration of Different Techniques on Heart Disease Prediction. In *2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech)* (pp. 758-764). IEEE.

[27] Gautam, V. K., Gupta, S., & Garg, P. (2024, March). Automatic Irrigation System using IoT. In *2024 International Conference on Automation and Computation (AUTOCOM)* (pp. 100-103). IEEE.

[28] Ramasamy, L. K., Khan, F., Joghee, S., Dempere, J., & Garg, P. (2024, March). Forecast of Students' Mental Health Combining an Artificial Intelligence Technique and Fuzzy Inference System. In *2024 International Conference on Automation and Computation (AUTOCOM)* (pp. 85-90). IEEE.

[29] Rajput, R., Sukumar, V., Patnaik, P., Garg, P., &Ranjan, M. (2024, March). The Cognitive Analysis for an Approach to Neuroscience. In *2024 International Conference on Automation and Computation (AUTOCOM)* (pp. 524-528). IEEE.

[30] Dixit, A., Sethi, P., Garg, P., Pruthi, J., & Chauhan, R. (2024, July). CNN-based lip-reading system for visual input: A review. In *AIP Conference Proceedings* (Vol. 3121, No. 1). AIP Publishing.

[31] Bose, D., Arora, B., Srivastava, A. K., & Garg, P. (2024, May). A Computer Vision-Based Framework for Posture Analysis and Performance Prediction in Athletes. In *2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE)* (pp. 942-947). IEEE.

[32] Singh, M., Garg, P., Srivastava, S., &Saggu, A. K. (2024, April). Revolutionising Arrhythmia Classification: Unleashing the Power of Machine Learning and Data Amplification for Precision Healthcare. In *2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT)* (pp. 516-522). IEEE.

[33] Kumar, R., Das, R., Garg, P., &Pandita, N. (2024, April). Duplicate Node Detection Method for Wireless Sensors. In *2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT)* (pp. 512-515). IEEE.

[34] Bhardwaj, H., Das, R., Garg, P., & Kumar, R. (2024, April). Handwritten Text Recognition Using Deep Learning. In *2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT)* (pp. 506-511). IEEE.

[35] Gill, A., Jain, D., Sharma, J., Kumar, A., & Garg, P. (2024, May). Deep learning approach for facial identification for online transactions. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 715-722). IEEE.

[36] Mittal, H. K., Dalal, P., Garg, P., &Joon, R. (2024, May). Forecasting Pollution Trends: Comparing Linear, Logistic Regression, and Neural Networks. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 411-419). IEEE.

[37] Malik, T., Nandal, V., & Garg, P. (2024, May). Deep Learning-Based Classification of Diabetic Retinopathy: Leveraging the Power of VGG-19. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 645-651). IEEE.

[38] Srivastava, A. K., Verma, I., & Garg, P. (2024, May). Improvements in Recommendation Systems Using Graph Neural Networks. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 668-672). IEEE.

[39] Aggarwal, A., Jain, D., Gupta, A., & Garg, P. (2024, May). Analysis and Prediction of Customer Churn and Retention Rates in the Telecom Industry Using Logistic Regression. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 723-727). IEEE.

[40] Mittal, H. K., Arsalan, M., & Garg, P. (2024, May). A Novel Deep Learning Model for Effective Story Point Estimation in Agile Software Development. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 404-410). IEEE.

[41] Shukla, S. M., Magoo, C., & Garg, P. (2024, November). Comparing Fine-Tuned LMs for Detecting LLM-Generated Text. In *2024, the 3rd Edition of IEEE Delhi Section Flagship Conference (DELCON)* (pp. 1-8). IEEE.

[42] Kumar, B., IQBAL, M., Parmer, R., Garg, P., Rani, S., & Agrawal, A. (2025, March). The Role of AI in Optimising Healthcare Appointment Scheduling. In *2025, the 3rd International Conference on Disruptive Technologies (ICDT)* (pp. 881-887). IEEE.

[43] Kumar, B., Garg, V., Ahmed, K., Garg, P., Choudhary, S., &Baniya, P. (2025, March). Enhancing Healthcare with Blockchain: Innovations in Data Privacy, Security, and Interoperability. In *2025, the 3rd International Conference on Disruptive Technologies (ICDT)* (pp. 932-938). IEEE.

[44] Raj, V., Prakash, B. K., Kumar, A., & Garg, P. (2024, December). Optimise the Time a Mercedes-Benz Spends on the Test Bench Using Stacking Ensemble Learning. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 445-450). IEEE.

[45] Kaushik, N., Kumar, H., Raj, V., & Garg, P. (2024, December). Proactive Fault Prediction in Microservices Applications Using Trace Logs and Monitoring Metrics. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 410-415). IEEE.

[46] Kumar, A. A., Sri, C. V., Bohara, K. S. K., Setia, S., & Garg, P. (2024, December). Capnivesh: Financing Platform for Startups. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 261-265). IEEE.

[47] Bhandari, P., Setia, S., Kumar, K., & Garg, P. (2024, December). Optimising Cross-Platform Development with CI/CD and Containerization: A Review. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 175-180). IEEE.

[48] Chaudhary, A., & Garg, P. (2014). Detecting and diagnosing a disease using a patient monitoring system. *International Journal of Mechanical Engineering And Information Technology*, *2*(6), 493-499.

[49] Malik, K., Raheja, N., & Garg, P. (2011). Enhanced FP-growth algorithm. *International Journal of Computational Engineering and Management*, *12*, 54-56.

[50] Garg, P., Dixit, A., &Sethi, P. (2021, May). Link Prediction Techniques for Opportunistic Networks using Machine Learning, in *Proceedings of the International Conference on Innovative Computing & Communication (ICICC)*.

[51] Garg, P., Dixit, A., &Sethi, P. (2021, April). Opportunistic networks: Protocols, applications & simulation trends. In *Proceedings of the International Conference on Innovative Computing & Communication (ICICC)*.

[52] Garg, P., Dixit, A., &Sethi, P. (2021). Performance comparison of fresh and spray & wait protocol through one simulator. *IT in Industry*, *9*(2).

[53] Malik, M., Singh, Y., Garg, P., & Gupta, S. (2020). Deep Learning in the Healthcare System. *International Journal of Grid and Distributed Computing*, *13*(2), 469-468.

[54] Gupta, M., Garg, P., Gupta, S., &Joon, R. (2020). A Novel Approach for Malicious Node Detection in Cluster-Head Gateway Switching Routing in Mobile Ad Hoc Networks. *International Journal of Future Generation Communication and Networking*, *13*(4), 99-111.

[55] Gupta, A., Garg, P., &Sonal, Y. S. (2020). Edge Detection-Based 3D Biometric System for Security of Web-Based Payment and Task Management Application. *International Journal of Grid and Distributed Computing*, *13*(1), 2064-2076.

[56] Garg, P., & Raman, P. K. (2011). Broadcasting Protocol & Routing Characteristics With Wireless ad-hoc networ s. *Int. J. Comput. Emg. Manag*, *12*(1), 36-40.

[57] Garg, P., Arora, N., & Malik, T. (2011). Capacity Improvement of Wi-MAX in the presence of Different Codes WI-MAX: Speed & Scope of the future. *IJCEM*, *12*.

[58] Garg, P., Saroha, K., &Lochab, R. (2011). Review of wireless sensor networks: architecture and applications. IJCSMS International Journal of Computer Science & Management Studies, 11(01), 2231-5268.

[59] Yadav, S., &Garg, P. Development of a New Secure Algorithm for Encryption and Decryption of Images.

[60] Dixit, A., Sethi, P., & Garg, P. (2022). Rakshak: A Child Identification Software for Recognising Missing Children Using Machine Learning-Based Speech Clarification. International Journal of Knowledge-Based Organisations (IJKBO), 12(3), 1-15.

[61] Shukla, N., Garg, P., & Singh, M. (2022). MANET Proactive and Reactive Routing Protocols: A Comparison Study. International Journal of Knowledge-Based Organisations (IJKBO), 12(3), 1-14.

[62] Arya, A., Garg, P., Vellanki, S., Latha, M., Khan, M. A., &Chhbra, G. (2024). Optimisation Methods Based on Soft Computing for Improving Power System Stability. *Journal of Electrical Systems*, *20*(6s), 1051-1058.

[63] Garg, P. (2025). Cloud security posture management: Tools and techniques. Technix International Journal for Engineering Research, 12(3).

[64] Tyagi, P., Sharma, S., Srivastava, A., Rajput, N. K., Garg, P., &Kumari, M. (2025). AI in Healthcare: Transforming Medicine with Intelligence. In the *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p4

[65] Garg, P., Bhatt, M., Parmar, R., &Arsalan, M. (2025). Generative AI: Evolution, Applications, Challenges, and Future Prospects. *Applications, Challenges, and Future Prospects (May 17, 2025)*.

[66] Garg, P., Saraswat, P., & Siddiqui, Z. (2025). AI & the Indian Stock Market: A Review of Applications in Investment Decision.https://doi.org/10.63169/GCARED2025.p10

[67] Garg, P., Sharma, S., Mittal, S., Tevatia, R., Tyagi, V. K., & Kapoor, S. (2025). Unlocking Workforce Potential: AI-Powered Predictive Models for Employee Performance Evaluation.https://doi.org/10.63169/GCARED2025.p21

[68] Shrivas, N., Kalia, A., Roy, R., Sharma, S., Garg, P., & Agarwal, G. (2025). OSINT: A Double-edged Sword. In the *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p22

[69] Garg, P., Aditi, A., & Roy, B. (2025). A System of Computer Network: Based On Artificial Intelligence.https://doi.org/10.63169/GCARED2025.p24

[70] Parmar, R., Kapoor, S., Saifi, S., & Garg, P. (2025). Case Study on Intelligent Factory Systems for Improving Productivity and Capability in Industry 4.0 with Generative AI. In the *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p28

[71] Singh, R., Sharma, R., Kumar, R., Nafis, A., Siddiqui, M. A. M., & Garg, P. (2025). Detection of Unauthorised Construction using Machine Learning: A Review. In the *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p30

[72] Garg, P., Kapoor, S., Singh, V., Sharma, S., &Ankita, A. (2025). A Bridge between Blockchain and Decentralised Applications Web3 and Non-Web3 Crypto Wallets.https://doi.org/10.63169/GCARED2025.p35

[73] Verma, M., Sharma, S., Garg, P., & Singh, A. (2025). The Hidden Dangers of Prototype Pollution: A Comprehensive Detection Framework. In the *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p36

[74] Sharma, A., Sharma, S., Garg, P., & Bhardwaj, P. (2025). LockTalk: A Basic Secure Chat Application. In the *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India.

[75] Arora, K., Bawane, R., Gupta, C., Ahmed, K., & Garg, P. (2025). Detection and Prevention of Cyber Attacks and Threats using AI. In the *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p38

[76] Garg, P., Dhruv, D., Rahman, A. A., Rai, A., Siddiqui, M., & Yadav, D. (2025). Easeviewer: An Esports Production Tool.https://doi.org/10.63169/GCARED2025.p46

[77] Garg, P., Lakshita, L., Mehwish, M., Nazia, N., & Ahmed, K. (2025). Emerging Trend in Computational Technology: Innovations, Applications, and Challenges. *Applications and Challenges (May 17, 2025)*. https://doi.org/10.63169/GCARED2025.p51

[78] Chauhan, S., Singh, M., & Garg, P. (2021). Rapid Forecasting of Pandemic Outbreak Using Machine Learning. *Enabling Healthcare 4.0 for Pandemics: A Roadmap Using AI, Machine Learning, IoT and Cognitive Technologies*, 59-73.

[79] Gupta, S., & Garg, P. (2021). An insight review on multimedia forensics technology. *Cyber Crime and Forensic Computing: Modern Principles, Practices, and Algorithms*, *11*, 27.

[80] Shrivastava, P., Agarwal, P., Sharma, K., & Garg, P. (2021). Data leakage detection in Wi-Fi networks. *Cyber Crime and Forensic Computing: Modern Principles, Practices, and Algorithms*, *11*, 215.

[81] Meenakshi, P. G., &Shrivastava, P. (2021). Machine learning for mobile malware analysis. *Cyber Crime and Forensic Computing: Modern Principles, Practices, and Algorithms*, *11*, 151.

[82] Nanwal, J., Garg, P., Sethi, P., & Dixit, A. (2021). Green IoT and Big Data: Succeeding towards Building Smart Cities. In *Green Internet of Things for Smart Cities* (pp. 83-98). CRC Press.

[83] Gupta, M., Garg, P., & Agarwal, P. (2021). Ant Colony Optimisation Technique in Soft Computational Data Research for NP-Hard Problems. In *Artificial Intelligence for a Sustainable Industry 4.0* (pp. 197-211). Springer, Cham.

[84] Magoo, C., & Garg, P. (2021). Machine Learning Adversarial Attacks: A Survey Beyond. *Machine Learning Techniques and Analytics for Cloud Security*, 271-291.

[85] Garg, P., Srivastava, A. K., Anas, A., Gupta, B., & Mishra, C. (2023). Pneumonia Detection Through X-Ray Images Using Convolution Neural Network. In *Advancements in Bio-Medical Image Processing and Authentication in Telemedicine* (pp. 201-218). IGI Global.

[86] Gupta, S., & Garg, P. (2023). 14 Code-based post-quantum cryptographic technique: digital signature. *Quantum-Safe Cryptography Algorithms and Approaches: Impacts of Quantum Computing on Cybersecurity*, 193.

[87] Prakash, A., Avasthi, S., Kumari, P., &Rawat, M. (2023). PuneetGarg 18 Modern healthcare system: unveiling the possibility of quantum computing in medical and biomedical zones. Quantum-Safe Cryptography Algorithms and Approaches: Impacts of Quantum Computing on Cybersecurity, 249.

[88] Gupta, S., & Garg, P. (2024). Mobile Edge Computing for Decentralised Systems. *Decentralised Systems and Distributed Computing*, 75-88.

[89] Gupta, M., Garg, P., & Malik, C. (2024). Ensemble learning-based analysis of perinatal disorders in women. In Artificial Intelligence and Machine Learning for Women's Health Issues (pp. 91-105). Academic Press.

[90] Malik, M., Garg, P., & Malik, C. (2024). Artificial intelligence-based prediction of health risks among women during menopause. *Artificial Intelligence and Machine Learning for Women's Health Issues*, 137-150.

[91] Garg, P. (2024). Prediction of female pregnancy complications using artificial intelligence. In *Artificial Intelligence and Machine Learning for Women's Health Issues* (pp. 17-35). Academic Press.

[92] Pokhrel, L., Arsalan, M., Rani, P., Garg, P., &Pinheiro, P. R. (2026). AI-Powered Healthcare Solutions: Bridging the Medical Gap in Underserved Communities Worldwide. In *Applied AI and Computational Intelligence in Diagnostics and Decision-Making* (pp. 57-86). IGI Global Scientific Publishing.

[93] Kapoor, S., Parmar, R., Sharma, N., Garg, P., & Singh, N. J. (2026). AI and Computational Intelligence in Healthcare: An Introductory Guide. In *Applied AI and Computational Intelligence in Diagnostics and Decision-Making* (pp. 1-26). IGI Global Scientific Publishing.

[94] Pokhrel, L., Kumar, A., Garg, P., Anand, N., & Singh, N. (2026). AI and IoT in Global Health: Ethical Lessons From Pandemic Response. In *Development and Management of Eco-Conscious IoT Medical Devices* (pp. 367-394). IGI Global Scientific Publishing.

[95] Parmar, R., Singh, A., Garg, P., Sharma, T., &Pinheiro, P. R. (2026). Blockchain for Ethical Supply Chains: Transparency in Medical IoT Manufacturing. In *Development and Management of Eco-Conscious IoT Medical Devices* (pp. 337-366). IGI Global Scientific Publishing.

[96] Gupta, S., Garg, P., Agarwal, J., Thakur, H. K., & Yadav, S. P. (2024). Federated learning-based intelligent systems to handle issues and challenges in IoVs (Part 1). https://doi.org/10.2174/9789815313031124030l

[97] Gupta, S., Chaudhary, G., & Garg, P. (2013). Modified AODV Routing Protocol through Cache Memory for Finding New Routing Paths in MANETs—International *Journal of Computer Science & Management Studies*, *13*(3).

[98] Gupta, A., & Garg, P. (2021). Emerging Techniques for Handling Pandemic Challenges. *Enabling Healthcare 4.0 for Pandemics: A Roadmap Using AI, Machine Learning, IoT and Cognitive Technologies*, 189-209.

[99] Chaudhary, A. P., Mishra, A., Kumar, D., & Garg, P. (2023, April). Human Emotion Recognition using Deep Learning. In the *2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN)* (pp. 191-197). IEEE.

[100]Nagpal, S., Garg, P., Gaba, S., & Aggarwal, A. (2023). 13 An improved genetic quantum cryptography model for network communication. *Quantum-Safe Cryptography Algorithms and Approaches: Impacts of Quantum Computing on Cybersecurity*, 177.

[101]Yadav, M., Swami, V., Kumar, N., & Garg, P. (2025). Comparative study of Repairable Juice Plants using RPGT. *Reliability: Theory & Applications*, *20*(2 (84)), 776-783.

[102]Gupta, A., Garg, P., & Yadav, P. (2025). Role of Generative AI Towards Education and Learning: Present & Future. *TPM–Testing, Psychometrics, Methodology in Applied Psychology*, *32*(S6 (2025): Posted 15 Sept), 1059-1076.

[103]Dalal, P., Beniwal, G., Sharma, V., Garg, P., & Ahmed, K. (2025). Predicting Student Motivation and Engagement through Machine Learning Models. *TPM–Testing, Psychometrics, Methodology in Applied Psychology*, *32*(S7 (2025): Posted 10 October), 393-411.

[104]Gupta, A., Mund, A., Roy, S., Garg, P., & Yadav, D. K. (2025). Trust in AI Systems: A Social-psychological Investigation of Human–AI Collaboration. *TPM–Testing, Psychometrics, Methodology in Applied Psychology*, *32*(S7 (2025): Posted 10 October), 428-446.

[105]Bhardwaj, A., Das, A., Garg, P., & Yadav, S. (2025). Material-Driven Performance Analysis of a Vertical Nanowire Tunnel FET for Analogue Applications: Bhardwaj, Das, Garg, and Yadav. *Journal of Electronic Materials*, 1-12.

[106]Dalal, P., Sharma, B., Sharma, T., Garg, P., & Ahmed, K. (2025). Explainable AI for Understanding Human Decision-Making Patterns. *TPM–Testing, Psychometrics, Methodology in Applied Psychology*, *32*(S7 (2025): Posted 10 October), 412-427.

[107]Sharma, K. K., Verma, P. K., Garg, P., &Shrotriya, V. K. (2025, October). Predicting costs and benefits of IoT-based energy management for optimising sustainable energy storage in rural areas. In *AIP Conference Proceedings* (Vol. 3343, No. 1, p. 040017). AIP Publishing LLC.

[108]Ahmed, K., Baranwal, A., Sharma, N., Garg, P., & Singh, N. (2026). The Role of Federated Learning in AI-Powered Integrated Healthcare Solutions. In *Enabling Collaborative Health Intelligence With Federated Learning* (pp. 421-448). IGI Global Scientific Publishing.

[109]Gupta, S., Garg, P., Agarwal, J., Thakur, H. K., & Yadav, S. P. (2025). Federated learning-based intelligent systems to handle issues and challenges in IoVs (Part 2). Bentham Science Publishers. https://doi.org/10.2174/9789815322241250301

[110]Garg, P., Pranav, S., &Prerna, A. (2021). Green internet of things (G-IoT): A solution for sustainable technological development. In *Green Internet of Things for Smart Cities* (pp. 23-46). CRC Press.

[111]Malik, A., Nandal, D., Gupta, V., Garg, P., &Nandal, V. INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING.

[112]Gupta, S., Garg, P., Agarwal, J., Thakur, H. K., & Yadav, S. P. (Eds.). (2025). Federated learning-based intelligent systems to handle issues and challenges in IoVs (Part 2).

[113]Garg, P., Bhatt, M., Parmar, R., &Arsalan, M. (2025). Generative AI: Evolution, Applications, Challenges, and Future Prospects. *Applications, Challenges, and Future Prospects (May 17, 2025)*.

[114]Kumar, N., Kumar, Y., Khurana, D., Kumar, S., & Garg, P. (2025, November). A Hybrid Ensemble Learning Framework for Interpretable Student Performance Prediction Using Academic and Extracurricular Factors. In *2025 International Conference on Innovations and Emerging Technologies in AI & Communication Systems (IETACS)* (pp. 666-672). IEEE.

[115]Khurana, D., Kumar, Y., Kumar, N., Kumar, S., & Garg, P. (2025, November). Transformer-Based Movie Recommendation System with Autoencoder-Enhanced Feature Compression. In *2025 International Conference on Innovations and Emerging Technologies in AI & Communication Systems (IETACS)* (pp. 685-690). IEEE.

[116]Garg, P. (2025, November). Comparative Analysis of Various Neural Networks for Galaxy Classification. In *2025 International Conference on Innovations and Emerging Technologies in AI & Communication Systems (IETACS)* (pp. 697-701). IEEE.

[117]Saggu, A. K., Babbar, N., & Garg, P. (2025, November). Health-Guard AI: Integrated Health Report Management and Analysis. In *2025 International Conference on Innovations and Emerging Technologies in AI & Communication Systems (IETACS)* (pp. 614-623). IEEE.

[118]Kumar, S., Kumar, Y., Kumar, N., Khurana, D., & Garg, P. (2025, November). Hybrid FCM-DNN Model for Uncertainty-Aware Air Quality Classification Using Multi-Pollutant Data. In *2025 International Conference on Innovations and Emerging Technologies in AI & Communication Systems (IETACS)* (pp. 679-684). IEEE.

[119]Babbar, N., Singh, H. V., Bendale, S., & Garg, P. (2025, November). Stock Market Price Prediction Using Big Data Analysis: A Performance Evaluation Study. In *2025, the 3rd International Conference on Computational Intelligence and Network Systems (CINS)* (pp. 1-6). IEEE.

[120]Singh, A. K., Kori, G., Garg, P., & Srivastava, G. (2025, November). Bank Churn Prediction Using Machine Learning. In *2025, IEEE 7th International Conference on Computing, Communication and Automation (ICCCA)* (pp. 1-6). IEEE.

[121]Bhardwaj, A., Das, A., Garg, P., & Yadav, S. (2026). Material-Driven Performance Analysis of a Vertical Nanowire Tunnel FET for Analogue Applications. *Journal of Electronic Materials*, *55*(1), 1099-1110.

[122]Srivastava, A. K., Shankdhar, D., Ror, R., & Garg, P. (2026). Harnessing YOLOv5 for real-time object detection: A cloud-based approach. In *Recent Advances in Computational Methods in Science and Technology* (pp. 441-450). CRC Press.

[123]Srivastava, A. K., Shukla, A., Gupta, H., Saxena, K., & Garg, P. (2026). Towards an intelligent attendance management system with face recognition using the LBPH algorithm. In *Recent Advances in Computational Methods in Science and Technology* (pp. 8-15). CRC Press.

[124]Srivastava, A. K., Garg, P., & Pandey, H. (2026). Vedcure: Towards intelligent ayurvedic drug recommendation and disease prediction. In *Recent Advances in Computational Methods in Science and Technology* (pp. 16-23). CRC Press.

[125]Upadhyay, D., Garg, P., &Babbar, N. (2026). Blockchain and IoT-based smart contract framework for efficient and secure product life management. *Discover Internet of Things*.

[126]Singh, A., Parmar, R., Bhardwaj, P., Sharma, V., & Garg, P. (2026). Fusion of Aerial Networks with Advanced Computing Paradigms. *Edge Computing and Aerial Platforms*, 355-367.

[127]Kumari, M., Baranwal, A., Sonal, & Garg, P. (2026). Application of Aerial Edge Computing in Disaster Management. *Edge Computing and Aerial Platforms*, 103-122.

[128]Aditi, Saraswat, P., Sharma, V., & Garg, P. (2026). Advances in Aerial Platforms and Edge Computing. *Edge Computing and Aerial Platforms*, 123-143.

[129]Garg, P., Arora, K., Bawane, R., Gupta, C., & Ahmed, K. (2025). Detection and Prevention of Cyber Attacks and Threats using AI.

[130]Ahmed, K., Ahmed, A., Khan, J., Garg, P., Seth, S., &Mallik, S. (2025). Principal Component Analysis-Based Clustering of Insecticides and Molecular Docking of Pyrethroid Insecticides.

[131]Kumar, B., Kumar, A., Nanwal, J., Garg, P., & Patnaik, P. (2025, November). Ensemble of YOLOv5 and Segment Anything Model for Brain Tumour Detection. In *2025, the 2nd International Conference on Advanced Computing and Emerging Technologies (ACET)* (pp. 1-5). IEEE.

[132]Arsalan, M., Anas, M., & Garg, P. (2025). Transparent AI for Drug Discovery and Development. *Available at SSRN 5844242*.

[133]Singh, A., Bhardwaj, P., Garg, P., & Singh, N. (2026). Introduction to explainable artificial intelligence in healthcare. In *Explainable AI in Clinical Practice* (pp. 23-44). Academic Press.

[134]Kapoor, S., Singh, A., Garg, P., &Ramasamy, L. K. (2026). Explainable artificial intelligence in a diagnostic support system. In *Explainable AI in Clinical Practice* (pp. 131-145). Academic Press.

[135]Ahmed, K., Anas, M., & Garg, P. (2026). Case studies on unlocking the potential of Industry 4.0 for sustainable manufacturing through generative AI-driven innovations. *Available at SSRN 6356958*.

[136]Garg, P., &Oruganti, S. K. (2026, March). AI Assisted Routing Optimisation in Opportunistic IoT Networks using Machine Learning: A Comprehensive Review on Protocols & Simulators. In *Sustainable Global Societies Initiative* (Vol. 1, No. 4). Vibrasphere Technologies.

[137]Arsalan, M., Pokhrel, L., & Garg, P. (2026). Architecture, Components, and tools in Integrated AI-Augmented Intelligence: A design perspective. *Components and tools in Integrated AI-Augmented Intelligence: A design perspective (March 19, 2026)*.

[138]Singh, H., Ahmed, K., & Garg, P. (2026). Human Versus Machine Customer Behaviour and Functional Differences. *Available at SSRN 6441098*.

[139]Saraswat, P., & Garg, P. (2026). Soft Computing In AI Agents.

[140]Saraswat, P., & Garg, P. (2026). Water Quality Prediction Using IOT Sensors and Deep Networks.

[141]Arsalan, M., Ahmed, K., & Garg, P. (2026). Machine learning for Anomaly detection in sensor networks. *Available at SSRN 6441518*.

[142]Kumari, M., & Garg, P. (2026). Hybrid Cloud Infrastructure: Models, Benefits, Security, and Challenges. *Benefits, Security, and Challenges (March 19, 2026)*.

[143]Singh, H., & Garg, P. (2026). Demystifying Artificial Distributed Intelligence (ADI). *Available at SSRN 6442698*.

[144]Saraswat, P., & Garg, P. (2026). Human-AI Collaboration: the future of clinical decision-making.

[145]Saraswat, P., & Garg, P. (2026). Breaking Data Boundaries: Federated Learning in Digital Healthcare.

[146]Singh, A., Parmar, R., Bhardwaj, P., Sharma, V., & Garg, P. (2026). Fusion of Aerial Networks with Advanced Computing Paradigms. *Edge Computing and Aerial Platforms*, 355-367.

[147]Kumari, M., Baranwal, A., Sonal, & Garg, P. (2026). Application of Aerial Edge Computing in Disaster Management. *Edge Computing and Aerial Platforms*, 103-122.

[148]Aditi, Saraswat, P., Sharma, V., & Garg, P. (2026). Advances in Aerial Platforms and Edge Computing. *Edge Computing and Aerial Platforms*, 123-143.

[149]Garg, P. (2026). Zero-Trust Security Enforcement through AI-Powered Anomaly Detection in Cloud Systems. *Journal of Artificial Intelligence in Governance and Public Policy (JAIGPP)*, *1*(1), 1-8.

[150]Singh, A. P., Sharma, A., & Garg, P. (2026, January). AI-Powered Adaptive Mock Interview Generation System. In *2026 International Conference on AI-Driven Smart Systems and Ubiquitous Computing (ICAUC)* (pp. 1421-1426). IEEE.

[151]Raghav, A., Mishra, A., & Garg, P. (2026, January). Enhancing Healthcare Access: An AI-driven Chatbot for Doctor Appointment Management. In *2026 International Conference on AI-Driven Smart Systems and Ubiquitous Computing (ICAUC)* (pp. 910-914). IEEE.

[152]Kumar, B., Chauhan, D., Singh, H., Verma, H., Sahu, K., & Garg, P. (2026, January). Decoding Linear A with Artificial Intelligence: A Comprehensive Machine Learning and NLP Framework. In *2026 International Conference on AI-Driven Smart Systems and Ubiquitous Computing (ICAUC)* (pp. 1-7). IEEE.

[153]Gupta, V., Chakravarti, L., Akhtar, M. M., Maheshwari, P., Garg, P., & Tiwari, D. (2026, January). A Sentence-Level Risk Estimator for Identifying Hallucinations in Generative AI. In *2026 International Conference on AI-Driven Smart Systems and Ubiquitous Computing (ICAUC)* (pp. 1619-1626). IEEE.

[154]Patnaik, P., & Garg, P. (2026). *Principles of Artificial Intelligence: Cognitive Architectures, Large Language Models, and Computational Limits*. Deep Science Publishing.

[155]Singh, K., & Garg, P. (2026). *Trustworthy Deep Learning: Robustness, Uncertainty Quantification, and Adversarial Resilience*. Deep Science Publishing.

[156]Garg, P. (2026). Survey of Load Balancing Strategies in Fog-Cloud Architectures for IoT Integration. *International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)*, *9*(2), 595-604.

[157]Tiwari, D., Bhati, B. S., Garg, P., &Babbar, N. (2026). A novel lexicon dictionary and CNN-LSTM employed hybrid approach for sentiment detection of COVID-19 vaccines. *Scientific Reports*.

[158]Sethi, P., Kumar, B., Garg, P., & Yadav, P. (2026, February). Graph Neural Networks for Causal Inference in Climate Science: A Novel Approach to Modelling Complex Interactions. In *2026 International Conference on Intelligent Computing and Automation for Sustainable Solutions (ICASS)* (pp. 1-7). IEEE.

[159]Kumar, B., Garg, P., Garg, A., Nanwal, J., & Yadav, P. (2026, February). An AI-Centric Multimodal Framework for Cognitive Productivity and Digital Wellbeing. In *2026 International Conference on Intelligent Computing and Automation for Sustainable Solutions (ICASS)* (pp. 1-7). IEEE.