International Journal
of
Research in Finance and Management

P-ISSN: 2617-5754
E-ISSN: 2617-5762
IJRFM 2025; 8(1): 116-118
www.allfinancejournal.com
Received: 15-12-2024
Accepted: 17-01-2025

Shivali Kukreja
Head of Risk,
Nib, New Zealand

Correspondence
Shivali Kukreja
Head of Risk,
Nib, New Zealand

Human bias in risk management: Cognitive limitations and decision-making in financial institutions

Shivali Kukreja

DOI: https://dx.doi.org/10.33545/26175754.2025.v8.i1b.432

Abstract
Cognitive biases are at work in risk perception, choice, and governance in financial entities. These biases—such as overconfidence, anchoring, and loss aversion—can distort risk assessment, leading to suboptimal financial and regulatory outcomes. This work analyzes the most common biases impacting business risk management (bRM) and investigates behavioral economics-driven interventions aimed at reducing them. Evidence-based on experimental studies, questionnaires from risk practitioners, and a review of previous risk failures show how organisations might establish systems and controls to mitigate bias. Results are used to advance behavioral risk management frameworks that leverage psychological knowledge into governance, increasing risk consciousness and statistical precision in judgments.

Keyword: Human bias, risk management, cognitive limitations

1. Introduction
Risk management in financial institutions is typically a quantitative model and regulatory compliance environment. However, human judgment plays a critical role in interpreting risk signals and making strategic decisions. On the basis of psychobiological studies, it can be deduced that cognitive distortions systematically shape the decision-making process and in principle imbalance either risk is not sufficiently valued or risk is overvalued. This paper investigates the kind of biases that can manifest in financial risk management and proposes ways of mitigating the undesirable effects of such biases.

Cognitive Biases in Risk Management
Cognitive biases can deceive risk appraisal and judgment to act/not act in various ways. One of the most pervasive mistakes in financial risk management are:

1.1 Overconfidence Bias
Overall altruism biases risk professionals to underemphasize potential threats to the self and overemphasize the predictive capabilities they will be able to hold about market movements. Research indicates that high overconfident traders and executives take undue risks, thereby exposing themselves to risk of financial fragility [1]. Overconfidence is often found to be accompanied by confirmation bias, and since, the confidence in false market direction trend beliefs is intensified. Developing and refining forecasting models is an arduous but important task for traders, bias can have several consequences on decision making in the wrong way, traders may be unaware of how to be wrong but these mistakes can cause them to assume higher financial risk exposure such as traders highly certain of their forecasting methods will probably try to find evidence that a prediction is true while ignoring evidence that suggests it may be wrong

1.2 Anchoring Bias
Risk assessments, however, commonly use initial starting points, independent of the availability of new evidence, which may be contradictory. This "anchoring effect" can lead financial analysts to stick with obsolete estimates (or risk estimates) and subsequently take

suboptimal investment and regulatory decisions [3]. In high-pressure situations, anchoring bias can further intensify the seductive effect of groupthink that suppresses contrary viewpoints [4].

1.3 Loss Aversion
The propensity to select against loss over select equivalent gains can result in risk managers utilizing too conservative of an approach. This bias is particularly problematic during a crisis when delayed decision-making exacerbates the economic crisis [5]. Loss aversion can also lead to hasty selling of assets, which will result in losses in the short term [6].

1.4Confirmation Bias
Decision-makers frequently look for information to validate their own beliefs while ignoring evidence to the contrary. In financial institutions, this may, for instance through design choice, result in underestimating the nascent risks, or not giving adequate weight to the early warning signals [7]. AI-powered analytics can be applied in order to circumvent confirmation bias by giving heterogeneous data sets and changing risk scenarios [8].

1.5 Herding Behavior
Herding bias drives professionals to rely on group agreement rather than performing independent risk evaluations. This could exacerbate systemic risks and result in financial bubbles or crises [9]. The adoption of the process of built-in conflict resolution can mitigate the tendency towards groupthink in financial decision-making.

2. Methodology
This work uses a mixed methods design to study financial risk management cognitive biases:

Experimental Studies: Participants (risk managers and financial managers, for example) will take part in dramatized risk scenarios. The decision-making accuracy will be the dependent variable and the independent variables will be exposure to cognitive bias provocations (e.g., misleading past trends). Bias measurement will be based on deviations from the ideal risk decisions and reaction times.

Surveys: A questionnaire in a structured form will be spread amongst the risk practitioners of the banking, insurance, and investment sectors. Questions will address the self-perception of susceptibility to biases, knowledge, and the real impact of bias-reduction tools. Sampling will be done according to a stratified random method to still reflect experience levels.

Case Study Analysis: Examples of historical financial risk liabilities, the 2008 financial crisis, and the Archegos Capital liquidation will be studied through the lens of a cognitive bias model. This framework will examine the consequences of strategic points of financial crisis decision making targeted biases. Tactics of bias manifested through selective data use, underestimation of risk, and postponing corrective actions will be drawn from financial reports, regulatory information disclosure, and corporate decision-tree records.

Mitigating Human Bias in Risk Management
Financial institutions have a range of options to try and reduce bias in risk assessment:

Behavioral Risk Management Frameworks
Applying behavioral science insights to the shape of governance mechanisms can enhance risk consciousness. These "nudging" techniques, and re-engineering of decision architecture have been shown to assist in reducing representational biases [10]. For example, shifting the default display regarding the probabilities of risks may be beneficial to make better decisions.

Implementing Structured Decision-Making Processes
With a view to refute for example, bias corporations should apply structured decision protocols and focus discussion on implementation and practical applications.

Pre-mortem Analysis: Encouraging risk teams to consider what may go wrong before making a decision.

Devil's Advocacy: Assigning a team to critically evaluate key risk assumptions.

Red Team Exercises: Simulation of unhealthy conditions for the evaluation of coping with cognitive biases [12].

If these kinds of steps can be assimilated within the context of financial decision-making, institutions are well-positioned to mitigate biases at t3 AI and Data-Driven Decision Support more effectively
Machine learning algorithms can be tools for supplementing human decision-making by highlighting biases in the risk modeling process. Automated anomaly detection and predictive analytics offer objective measures that minimize subject-to-subject decision-making [11]. In addition, AI-based dashboards can also be applied together with counterfactual situations allowing current risk assumptions to be questioned. AI can also offer:

Personalized Interventions: Adaptive algorithms are able to vary the bias-mitigation measures based on the track record of decision in the subject and susceptibility to cognitive biases.

Real-time Feedback: Decision errors attributable to bias can be corrected by AI-based training simulations, and can be corrected in the present by real-time feedback, thereby improving long-term professional judgment.

Explainable AI (XAI): Ultimately, XAI achieves this through enhanced transparency, where the meaning of the seemingly complex models can be explained and trusted AI-based risk estimates can be promoted.

Fostering an Organizational Culture of Critical Thinking
Critical thought, independent examination, and pluralistic point of view should be encouraged in financial institutions. The implementation of psychological safety strategies is not a promise to the employees that their voices will be heard freely and without fear of judgment for challenging the

group consensus. Leadership should actively encourage constructive dissent and debate (14). Specific mechanisms include:

Leadership Role: Senior management should practice open dialogue and healthy constructive criticism.

Incentive Structures: Performance incentives should align with mechanisms of performance through extensive risk scrutiny instead of the quick-profit paradigm.

Communication Strategies: In designing debates and challenge sessions, it is possible to bypass groupthink and promote autonomous thinking their core.

3. Conclusion

Cognitive biases play a central role in risk, decision, and regulatory compliance in finance. Through embedding behavioral economic bounds on risk estimate accuracy, the accuracy of risk estimation is enhanced to the detriment of systemic risk and financial institutions. Further research is indicated for (a) interventions based on AI for reducing bias, and (b) culture and risk appraisal.

4. Limitations

This study has certain limitations that should be acknowledged.

Methodological Constraints: Such experimental designs may not be sufficient to reconstruct the genuine "realness" of real financial decision-making.

Generalizability: Outcomes may be industry-specific and not be generalizable to other industries.

Data Availability: Coincidentally the specificity of the history data and reporting will actually be the foundation for the gained insight from case studies.

5. References

1. Barber BM, Odean T. Boys will be boys: Gender, overconfidence, and common stock investment. Q J Econ. 2001;116(1):261-292.
2. Nickerson RS. Confirmation bias: A ubiquitous phenomenon in many guises. Rev Gen Psychol. 1998;2(2):175-220.
3. Kahneman D, Tversky A. Prospect theory: An analysis of decision under risk. Econometrica. 1979;47(2):263-291.
4. Shiller RJ. Irrational exuberance. Princeton University Press; c2000.
5. Bengio Y, Lodi A, Prouvost A. Machine learning for combinatorial optimization: A methodological tour d’horizon. Eur J Oper Res. 2021;290(2):405-421.
6. Sunstein CR. Why nudge? The politics of libertarian paternalism. Yale University Press; c2014.
7. Thaler RH, Sunstein CR. Nudge: Improving decisions about health, wealth, and happiness. Yale University Press; c2008.
8. Tversky A, Kahneman D. The framing of decisions and the psychology of choice. Science. 1981;211(4481):453-458.
9. Kahneman D. Thinking, fast and slow. Farrar, Straus, and Giroux; c2011.
10. Ariely D. Predictably irrational: The hidden forces that shape our decisions. HarperCollins; c2008.
11. Tetlock PE, Gardner D. Superforecasting: The art and science of prediction. Crown Publishing Group; c2015.
12. Taleb NN. The Black Swan: The impact of the highly improbable. Random House; c2007.
13. Loewenstein G, Lerner JS. The role of affect in decision making. In: Davidson RJ, Goldsmith H, Scherer K, editors. Handbook of Affective Science. Oxford University Press; 2003. p. 619-642.
14. Edmondson AC. The fearless organization: Creating psychological safety in the workplace for learning, innovation, and growth. Wiley; c2018.