

## **Decoding investor psychology : The role of robo-advisors in mitigating herding bias and fear of missing out**

Manisha Manchanda <sup>§</sup>

Ayush <sup>†</sup>

Himanshi Bajaj <sup>\*</sup>

*Department of Management Studies*

*Deenbandhu Chhotu Ram University of Science and Technology*

*Murthal 131027*

*Haryana*

*India*

Swati <sup>‡</sup>

*Department of Commerce*

*Govt. College Hathin (Palwal)*

*Hathin 121103*

*Palwal*

*Haryana*

*India*

---

### **Abstract**

In traditional finance, it is presumed that investors are rational, but behavioral finance totally contradicts the idea that investors are rational. In reality, investors are emotional, which influences investment choices, including sentiments, peer pressure, and informational noise. Investors' decisions are affected by many biases that cause investors to act illogically, which often results in noise trading. With the evolution of modern finance, Artificial Intelligence (AI) and Behavioral Finance have gained significant attention, resulting increased in the trend of robo-advisors. Robo-advisors assist investors in making decisions by providing algorithm-driven, emotion-free investment recommendations, which are emerging as a potential buffer against such biases. However, very few studies portray robo-advisory platforms as

---

<sup>§</sup> ORCID-ID: 0000-0003-3931-3699

<sup>†</sup> ORCID-ID: 0009-0009-4129-917X

<sup>\*</sup> ORCID-ID: 0009-0005-2321-0486

<sup>‡</sup> ORCID-ID: 000-0002-9321-6729

---

<sup>§</sup> E-mail: manisha.mba@dcrustm.org

<sup>†</sup> E-mail: ayushchanana0612@gmail.com

<sup>\*</sup> E-mail: himanshibajaj612@gmail.com (Corresponding Author)

<sup>‡</sup> E-mail: swati.jangra77@gmail.com

moderators among behavioral biases. Therefore, to address this gap, data was collected from 393 investors with the help of Google Forms using purposive sampling technique. Structural Equation Modelling (SEM) using Analysis of Moment Structures 22 (AMOS 22) was employed for data analysis. Findings revealed that Fear of Missing Out (FOMO) and herding bias significantly influence investors' Investment Decision-Making (IDM), while robo-advisory platforms are insufficient to eliminate these biases.

---

*Subject Classification:* 68T20, 68T40, 97M70.

*Keywords:* Artificial intelligence (AI), Behavioral biases, Fear of missing out (FOMO), Fintech, Herding, Investment decision making (IDM), Robo-advisors.

## 1. Introduction

Indeed, artificial intelligence (AI) is revolutionizing numerous industries, and it has a notable effect on wealth management [1]. With the emergence of AI technology, financial services have become more convenient and efficient [2]. The accelerated digitization of financial services has, in turn, enabled the integration of AI-powered instruments, known as 'robo-advisors'. These advisory services are online investment frameworks that utilize machine learning and AI to provide portfolio advisory services and personalized financial advice. However, robo-advisors facilitate Investment Decision Making (IDM) by delivering automated, algorithm-driven financial advice [3]. There are many biases that influence decision making of investors, which cause irrational behavior, resulting in suboptimal investment choices and increased market volatility [4]. Whereas two of the most prevalent biases, i.e., herd mentality and Fear of Missing Out (FOMO), influence investors' actions during the IDM process. Irrational market fluctuations are often amplified by both of these biases. The tendency of investors to imitate group behavior instead of making their own decisions is known as "herding" [5], [6].

Herd behavior is often observed in the financial market, where a significant degree of ambiguity exists, and individuals believe that others possess superior information [7]. Therefore, this behavior plays a critical role in financial market behavior, which leads to significant deviations in asset pricing. Moreover, this bias has been linked to FOMO in the investment context [8]. FOMO reflects a sense of anxiety in which individuals feel fear of missing opportunities that others are perceived to be experiencing [9]. Further, this bias has been linked to the formation of price bubbles in the market.

Various strategies have been used to mitigate biases & to improve the functioning of the market, which include financial literacy and reducing information asymmetry [10]. Robo advisors are also one of the most prominent strategies, which is an online platform that reduces biases improve the decision-making of investors through its algorithm mechanism [11].

## 2. Review of literature

Previous studies suggest that social media significantly multiplies herding tendencies through influencer credibility [12], where the bias significantly

influences Generation Z (Gen Z) investors' IDM [13] and also affects cryptocurrency investors' purchasing behavior [14]. Contrary to the view, certain prior studies have found no significant relationship between this bias and investors' decision-making [15], [16]. Closely aligned to herding behavior, prior studies demonstrated that FOMO significantly influences investor behavior in financial markets [8], [17] and is also associated with increased stress and suboptimal decision-making among investors [18]. Further, social media increases FOMO and reinforces crowd-following behavior, which can lead to asset bubbles and market instability, especially among younger investors [19].

Robo-advisors and other automated investment systems can help investors to overcome these biases while making investment decisions [9] by providing online services that handle investors' money without the need for human involvement [9]. Similar to human advisors, robo-advisors make suggestions that meet investors' requirements, which offer users advisory services, gather data about their investing goals, risk tolerance, return expectations, and loss tolerance, etc. By offering customized investment plans, a robo-advisor supports investors in overcoming herding bias, which helps them make more informed decisions rather than chasing market trends, resulting in sustained wealth accumulation [20]. Additionally, algorithm-based technology can perform complex computations, making this service cost-effective and enhancing information discovery. Robo-advisors prevent excessive trading by providing AI-based nudges [21].

### **3. Research Gap**

Earlier research examined the application of robo-advisors in the investment sector, but the evidence regarding their influence on social and emotional biases is limited. Addressing this gap, the present study seeks to examine investor psychology by analyzing the extent to which a robo-advisor can mitigate behavioral biases in IDM.

### **4. Objectives**

To examine the impact of herding bias, FOMO, & robo-advisors on IDM of individual investors, and further to know how robo-advisors moderate the relationship between the biases and individual investors' IDM.

### **5. Limitations of the study**

The present study contains some shortcomings, despite its contribution. First, the study merely focused on two biases only; many other biases are also influential in IDM. Second, the study is restricted to Delhi & National Capital Region (NCR) region investors, which may also restrict the generalisation of the findings.

### **6. Methodology**

#### *Research Design*

To gain insights into behavioral patterns of the investors current study employs quantitative analysis by using a descriptive research design.

### *Data Collection Method*

The current study employs primary data to address the research questions for which a structured, closed-ended questionnaire was created and distributed to each participant via Google Form. The questionnaire was structured into two distinct sections. ‘Section A’ includes respondents’ demographics, & ‘Section B’ consists of various constructs included in the study.

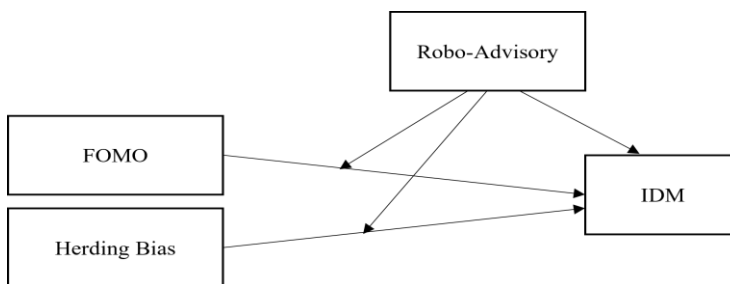
### *Sampling Design*

A sample size of 393 individual investors from Delhi NCR was taken. This region was specifically targeted because it represents one of India’s most prominent investment hubs, with a diversity of investor groups. A purposive sampling technique was used to collect data. Cochran’s formula was used to determine the sample size [22]. The actual number of responses (393) exceeded the suggested sample size (384).

### *Instrument Development*

This study took two independent variables, namely herding bias and FOMO, one dependent variable, namely IDM, and a robo-advisor as a moderating variable. For assessing herding bias, sub-constructs relating to information characteristics, namely argument quality and source credibility [23], and statements related to FOMO were calculated using a well-developed scale [24]. The dependent variable was measured using five items, where “dependent decision-making style” was used as a representative for calculating the IDM construct [25]. The moderating role of robo-advisors was operationalized using a scale [2] to maintain consistency with previous empirical research in the field of digital financial advice. The conceptual relationships among the study variables are shown in Figure 1.

### **Conceptual Framework**



Source: Constructed by authors

**Figure 1**  
**Conceptual model**

### *Hypotheses*

H1: Herding bias significantly influences individual investors' IDM.

H2: FOMO significantly influences individual investors' IDM.

H3: Robo-advisory significantly influences individual investors' IDM.

H4: Robo-advisor significantly moderates the relationship between herding bias and individual investors' IDM.

H5: Robo-advisor significantly moderates the relationship between FOMO and individual investors' IDM.

## 7. Data Analysis

The influence of three psychological factors (herding bias, FOMO, and robo-advisory) on IDM is examined using Structural Equation Modelling. Each latent construct is connected to its observed variables, and error terms are attached to each observed variable.

**Table 1**  
**Model Fit Summary: Chi-Square Statistics**

| Model              | Number of Parameters (NPAR) | Minimum Discrepancy (Chi-Square) Statistic (CMIN) | Degrees of Freedom (DF) | P    | CMIN/DF |
|--------------------|-----------------------------|---------------------------------------------------|-------------------------|------|---------|
| Default model      | 75                          | 815.439                                           | 331                     | .000 | 2.464   |
| Saturated model    | 406                         | .000                                              | 0                       |      |         |
| Independence model | 28                          | 6430.080                                          | 378                     | .000 | 17.011  |

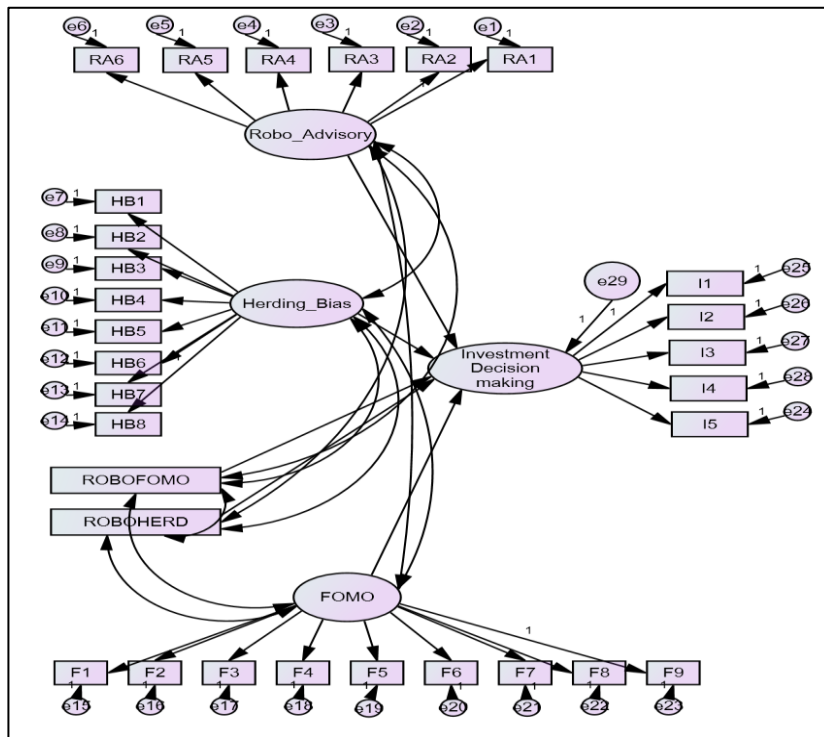
Source: Output from primary data

**Table 2**  
**Model Fit Indices**

| Model         | Goodness of Fit Index (GFI) | Comparative Fit Index (CFI) | Normed Fit Index (NFI) | Root Mean Square Error of Approximation (RMSEA) |
|---------------|-----------------------------|-----------------------------|------------------------|-------------------------------------------------|
| Default Model | 0.871                       | 0.920                       | 0.873                  | 0.061                                           |

Source: Output from primary data

Table 1 and Table 2 demonstrate an acceptable fit to the data where  $\chi^2$  (331) = 815.439,  $p < .001$ ; CMIN/DF = 2.464; GFI = 0.871; CFI = 0.920; NFI = 0.873; RMSEA = 0.061. While the GFI was slightly below the recommended threshold of 0.90, all other indices were within acceptable limits, suggesting that the model offers a satisfactory explanation of the observed data.



Source: Author's own compilation

**Figure 2**  
Structural model assessment

Figure 2 presents the structural model assessment stating the relationships among Robo-Advisory, Herding Bias, FOMO, and IDM, along with the moderating effects.

**Table 3**  
Regression Weights and Results of Hypothesis Testing

| S.No.          | Predictor → Outcome | Estimate ( $\beta$ ) | p-value | Decision |
|----------------|---------------------|----------------------|---------|----------|
| H <sub>1</sub> | Herding bias → IDM  | 0.103                | 0.042   | Accepted |
| H <sub>2</sub> | FOMO → IDM          | 0.813                | 0.000   | Accepted |
| H <sub>3</sub> | Robo advisory → IDM | -0.084               | 0.058   | Rejected |
| H <sub>4</sub> | Roboherd → IDM      | 0.26                 | 0.272   | Rejected |
| H <sub>5</sub> | Robofomo → IDM      | -0.73                | 0.002   | Rejected |

Source: Output from primary data

Table 3 shows that H1 is supported, showing that herding bias positively and significantly impacts individual investors' IDM ( $\beta=0.103$ ,  $p=0.042$ ). H2 is also accepted, showing a strong, significant, and positive impact of FOMO on IDM of individual investors ( $\beta=0.813$ ,  $p=0.001$ ). In contrast, H3 is rejected, where robo-advisory showed no significant impact on IDM of individual

investors ( $\beta=-0.084$ ,  $p=0.058$ ). Furthermore, H4 and H5 are also rejected ( $\beta=0.26$ ,  $p=0.272$ ;  $\beta=-0.73$ ,  $p=0.002$ ), which shows that the robo advisor as a moderator does not help mitigate these biases.

## 8. Discussion

From this study, it is clearly observed that individual investors' IDM is majorly influenced by behavioral bias, which is also supported by a previous study. Indeed, FOMO has emerged as a dominant driver in taking impulsive decisions, where investors are notably being influenced by emotional triggers (peer comparison and market trend). Moreover, herding bias also significantly impacts IDM, which indicates that group behavior influences each other, which is supported by the previous study [7].

Conversely, robo-advisory showed no significant impact on individual investors' investment decisions because investors have limited reliance on robo-advisory platforms due to a lack of trust and novelty. Therefore, the algorithm-based robo-advisors are not sufficient to address these social biases among decision makers; Indeed, this study contributes to the literature that technology offers various benefits, but its effectiveness in reducing these biases is limited.

Overall, the results demonstrate that biases have a significant impact on investors' IDM; conversely, it also challenges the idea that robo advisor helps in mitigating these biases.

## 9. Conclusion, implications, and recommendations

The present study has contributed to the potential areas where there is a need to refine the robo advisory model to better mitigate the behavioral bias and enhance rational decision-making. Though investors should not substitute the robo-advisor for critical judgment, but investors should use the robo-advisors as a complementary tool that provides structured advice, and they need to remain aware of their own behavioral biases so that they can take more balanced, informed, or rational decisions. Additionally, financial advisors can improve the robo-advisor model that integrates behavioral nudges, educational content, and personalized features. Further, regulators can help investors by maintaining cybersecurity standards, which can help investors make wise decisions. Future studies may include other biases and broaden the geographical and cultural context to improve generalizability.

## References

- [1] D. Leone, F. Schiavone, F. P. Appio, and B. Chiao, "How does artificial intelligence enable and enhance value co-creation in industrial markets? An exploratory case study in the healthcare ecosystem," *J. Bus. Res.*, vol. 129, no. 2, pp. 849–859 (May 2021), doi: 10.1016/j.jbusres.2020.11.008.

- [2] D. Belanche, L. V. Casaló, and C. Flavián, "Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers," *Industrial Management & Data Systems*, vol. 119, no. 7, pp. 1411–1430 (2019), doi: 10.1108/IMDS-08-2018-0368.
- [3] I. Nain, S. Rajan, N. Natchimuthu, and G. Shivanna, "An empirical analysis of the antecedents and barriers to adopting robo-advisors for investment management among Indian investors," *Macroeconomics and Finance in Emerging Market Economies*, vol. 19, no. 2, pp. 391–408 (Apr. 2024), doi: 10.1080/17520843.2024.2341530.
- [4] N. Sathya and R. Gayathiri, "Behavioral Biases in Investment Decisions: An Extensive Literature Review and Pathways for Future Research," *J. Inf. Organ. Sci.*, vol. 48, no. 1, pp. 117–131 (Jun. 2024), doi: 10.31341/jios.48.1.6.
- [5] M. Baddeley, "Herding, social influence and economic decision-making: socio-psychological and neuroscientific analyses," *Phil. Trans. R. Soc. B*, vol. 365, no. 1538, pp. 281–290 (Jan. 2010), doi: 10.1098/rstb.2009.0169.
- [6] A. Sao, A. Kumar, N. Bhasin, Savita, and M. Sharma, "Evolution of online herd behavior of investors in Indian stock market," *J. Inf. Optim. Sci.*, vol. 44, no. 8, pp. 1649–1664 (2023), doi: 10.47974/JIOS-1482.
- [7] B. Fernández, T. Garcia-Merino, R. Mayoral, V. Santos, and E. Valledado, "Herding, information uncertainty and investors' cognitive profile," *Qualitative Research in Financial Markets*, vol. 3, no. 1, pp. 7–33 (Apr. 2011), doi: 10.1108/17554171111124595.
- [8] S. Gupta and M. Shrivastava, "Herding and loss aversion in stock markets: mediating role of fear of missing out (FOMO) in retail investors," *IJOEM*, vol. 17, no. 7, pp. 1720–1737 (2022), doi: 10.1108/ijoem-08-2020-0933.
- [9] A. K. Przybylski, K. Murayama, C. R. DeHaan, and V. Gladwell, "Motivational, emotional, and behavioral correlates of fear of missing out," *Comput. Human. Behav.*, vol. 29, no. 4, pp. 1841–1848 (Jul. 2013), doi: 10.1016/j.chb.2013.02.014.
- [10] A. Bhatia, A. Chandani, R. Divekar, M. Mehta, and N. Vijay, "Digital innovation in wealth management landscape: the moderating role of robo advisors in behavioural biases and investment decision-making," *IJIS*, vol. 14, no. 3/4, pp. 693–712 (2022), doi: 10.1108/ijis-10-2020-0245.

- [11] F. D'Acunto and A. G. Rossi, "Households' behavioral biases: Is robo-advice a solution?," in *Oxford Research Encyclopedia of Economics and Finance*. Oxford, U.K.: Oxford Univ. Press, 2024. doi: 10.2139/ssrn.4666240.
- [12] L. G. H. Singh and K. Kumar, "The herding behavior of investors in the Indian financial market: An insight into the influence of social media," in *Research on Innovative Approaches to Information Technology in Library and Information Science*. Hershey, PA, USA: IGI Global, ch. 5 (2024), doi: 10.4018/979-8-3693-0807-3.ch005.
- [13] H. Maheshwari and A. K. Samantaray, "Beyond instinct: the influence of artificial intelligence on investment decision-making among Gen Z investors in emerging markets," *International Journal of Accounting & Information Management*, vol. 34, no. 1, pp. 174–192 (Jan. 2025), doi: 10.1108/ijaim-10-2024-0371.
- [14] Y. H. Wijaya and H. W. S. Elgeka, "Herding Behavior and Its Impact on Purchasing Decisions Among Beginner Crypto Investors: An Experimental Analysis," *gamajop*, vol. 10, no. 2, p. 91 (Oct. 2024), doi: 10.22146/gamajop.84536.
- [15] R. Gurung, R. Kumar Dahal, B. Ghimire, and N. Koirala, "Unraveling behavioral biases in decision making: A study of Nepalese investors," *Investment Management and Financial Innovations*, vol. 21, no. 1, pp. 25–37 (Jan. 2024), doi: 10.21511/imfi.21(1).2024.03.
- [16] A. Kumari, R. Goyal, and S. Kumar, "Analytical study of behavioral dimensions of retail investors towards investment decision making & performance in stock market," *Journal of Information and Optimization Sciences*, vol. 44, no. 3, pp. 417–425 (2023), doi: 10.47974/JIOS-1358.
- [17] S. Güngör, N. Tomris Küçün, and K. Erol, "Fear of Missing Out Reality in Financial Investments," *International Journal of Business & Management Studies*, vol. 3, no. 10, pp. 53–59 (2022), doi: 10.56734/ijbms.v3n10a4.
- [18] M. Milyavskaya, M. Saffran, N. Hope, and R. Koestner, "Fear of missing out: prevalence, dynamics, and consequences of experiencing FOMO," *Motiv. Emot.*, vol. 42, no. 5, pp. 725–737 (Mar. 2018), doi: 10.1007/s11031-018-9683-5.
- [19] H. Idris, "The Effects of FOMO on Investment Behavior in the Stock Market," *GRDIS*, vol. 4, no. 2, pp. 879–887 (Oct. 2024), doi: 10.52970/grdis.v4i2.757.

- [20] A. Banerjee, R. P. Kumar, and R. Mohnot, "Embedding behavioral biases into robo-advisory platforms-case of UAE investors," *JRF*, vol. 26, no. 1, pp. 41–55 (2025), doi: 10.1108/jrf-06-2024-0184.
- [21] C. Hildebrand and A. Bergner, "Conversational robo advisors as surrogates of trust: onboarding experience, firm perception, and consumer financial decision making," *J. of the Acad. Mark. Sci.*, vol. 49, no. 4, pp. 659–676 (2021), doi: 10.1007/s11747-020-00753-z.
- [22] W. G. Cochran, *Sampling Techniques*, 3rd ed. New York, USA: John Wiley & Sons (1977).
- [23] G. Rejikumar, A. Asokan-Ajitha, S. Dinesh, and A. Jose, "The role of cognitive complexity and risk aversion in online herd behavior," *Electron Commer Res*, vol. 22, no. 2, pp. 585–621 (2022), doi: 10.1007/s10660-020-09451-y.
- [24] S. Clor-Proell, R. D. Guggenmos, and K. M. Rennekamp, "Mobile Devices and Investment Apps: The Effects of Push Notification, Information Release, and the Fear of Missing Out," *SSRN Journal*, pp. 1–46 (2017), doi: 10.2139/ssrn.2991262.
- [25] S. G. Scott and R. A. Bruce, "Decision-Making Style: The Development and Assessment of a New Measure," *Educ. Psychol. Meas.*, vol. 55, no. 5, pp. 818–831 (Oct. 1995), doi: 10.1177/0013164495055005017.

*Received December, 2025*