Artificial Intelligence in Fintech: Behavioural Factors Influencing Robo-Advisor Adoption

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The FinTech sector is being transformed by AI-powered robo-advisors. This study identifies and prioritizes factors influencing robo-advisor adoption for financial decision-making. Six factors were identified through exploratory factor analysis based on responses from 352 stock investors: trust, financial knowledge, performance and effort expectancy, perceived usability, herding and social influence, and attitude towards AI. These were ranked using fuzzy decision-making trial and evaluation laboratory technique, with trust, financial knowledge, and herding and social influence as the causes influencing other factors. This study contributes by integrating behavioural biases, particularly herding and social influence, into technology adoption frameworks, offering insights for developers.

Keywords: Robo-advisors, Behavioural Biases, Fintech

1. Introduction

The FinTech sector is witnessing a profound upheaval due to the growing commercialization of investing services powered by artificial intelligence, or "robo-advisors" (Arslanian and F. Fischer, 2019). Robo-advisors are online financial advisory systems that deliver financial suggestions through advanced algorithms (Park et al., 2016). Originally focused on basic portfolio design, these services have expanded to incorporate advanced financial product research [3]. They provide automated portfolio management with minimum human intervention, satisfying the desire for low-cost investment solutions (Ponnaiya and K. Ryan, 2017). Robo-advisors have gained appeal in both the financial sector and academia because to their low cost and efficiency (Park et al., 2016; Belanche et al., 2019; Hohenberger et al., 2019; Lourenco et al., 2020; Ruhr et al., 2019). However, there is little awareness of their uptake in developing nations, as well as a lack of clarity about the factors that influence adoption. This study aims to explore the behavioural factors that propel the uptake of robo-advisors, prioritize these factors, and determine the cause-effect relationships among them. This study is novel, as it is the first among developing nations and pioneers the effort to identify, find priority and cause-effect relationships among these factors. The insights from this study could significantly inform strategies to enhance the adoption and efficacy of robo-advisors in emerging markets.

2. Literature Review

The economy, society, and labour are all being predominantly influenced by the startling rise of artificial intelligence (AI) and robot-based systems across industries (Acemoglu and Restrepo, 2020). Robo-advisors, defined as "digital platforms encompassing immersive and intelligent assistive components that employ information technology to guide investors through a robotized investment advisory process," are part of this revolutionary paradigm (Jung et al., 2018). Research on robo-advisors draws on financial consulting and decision assist literature (Jung et al., 2018). The effects of design elements and personalization have been studied about customer interaction with robo-advisors (Glaser et al., 2019; Ruf et al., 2015). Trust appears as an important aspect in the use of robo-advisory services. Lee (Lee et al., 2018) highlight the importance of trust and information quality, which is corroborated by Jung (Jung et al., 2018), who discovered that trustworthiness has a considerable impact on user sentiments. Furthermore, Jung (Jung et al., 2018) indicated that trustworthy interaction is just as critical as effective outcomes in robo-advisory adoption. One more crucial prerequisite for trust is perceived danger. Studies have continually demonstrated a link between perceived risk and trust in technology (Malaquias and Y. Hwang, 2016; Roca et al., 2009). This is particularly pertinent in robo-advisory, where financial information is susceptible to fraud, increasing customer uncertainty (Roca et al., 2009; Heinrich and Schwabe, 2018). Bruckes (Bruckes, 2019) discovered that first-time digital investors are frequently disputing their judgments. Prior financial experience affects investors' propensity to use robo-advisors. Epperson (Epperson, 2015) found that experienced investors are more likely to employ these services. Hohenberger (Hohenberger et al., 2019) stated that robo-advisors aid persons unfamiliar with investing by automating judgments. Performance expectancy and perceived risk are both significant predictors of behavioural intention, with high performance expectancy caused by algorithm use leading to strong behavioural intentions (R¨uhr et al., 2019). Cheng (Cheng and Jiang, 2020) highlighted perceived utility, happiness, and flow experience as factors influencing sustained robo-advisor use. Milani (Milani, 2019) discovered that adoption intentions are positively correlated with education, experience in investing, and knowledge of robo-advisors; behavioural intention is also favourably influenced by perceived relative advantage, effort expectation, social influence, and trust, all of which are expressed by attitude. Lourenco (Lourenco et al., 2020) and Gan (Gan et al., 2021) back up these findings, with Lourenco identifying trust and expertise as key acceptance predictors and Gan emphasizing performance expectancy, social influence, and trust, particularly during the pandemic, as drivers of consumer intention to use robo-advisors. Robo-advisors are now frequently employed to assist investors in building diversified portfolios. Nevertheless, the idea is still relatively new, and the hurdles associated with robo-advisors have not been thoroughly studied. There is a significant research gap on the use of financial robo-advisors in developing countries, as a great deal of studies have been conducted in the US and Europe. Furthermore, the behavioural aspects driving the adoption of robo-advisers are not well understood.

3. Research Methodology

This study employs a novel hybrid methodology that combines two distinct approaches, fuzzy decision making trial and evaluation laboratory technique (F-DEMATEL) and exploratory factor analysis (EFA), to fully assess the factors impacting adoption of robo-advisors. The research is conducted in three phases that are carefully planned to provide important insights into the intricate dynamics of robo-advisor adoption. Firstly, a thorough literature review (LR) is carried out to find a variety of behavioural aspects that are known to affect robo-advisor acceptance. This step ensures that a complete collection of indicators drawn from previous studies and theoretical frameworks are included and lays the groundwork for further analysis. Subsequently, exploratory factor analysis (EFA) will be used in the second stage of the study to group the behavioural indicators that were found into separate components. EFA makes use of original data from 352 Indian individual stock investors chosen by purposive sampling. This allows for the methodical arrangement and classification of these indicators into key factors. This stage clarifies the underlying structures and linkages between the detected indicators in addition to facilitating the reduction of data complexity. Ultimately, the third phase of the research is conducted in two concurrent procedures, with guidance from ten domain experts. First, factors are ranked in order of priority by experts who determine the relative significance and importance of each element in determining the adoption of robo-advisors. concurrently, the F-DEMATEL technique is employed to investigate cause-and-effect correlations among the identified factors, thereby revealing the complex interrelationships and dependencies among them. This study aims to contribute to theoretical advancements and practical insights in the field of financial technology (FinTech) by offering a thorough understanding of the multifaceted factors influencing robo-advisor adoption through the seamless integration of these methodologies across the three stages. The research outline for this study is depicted in Fig. 1.

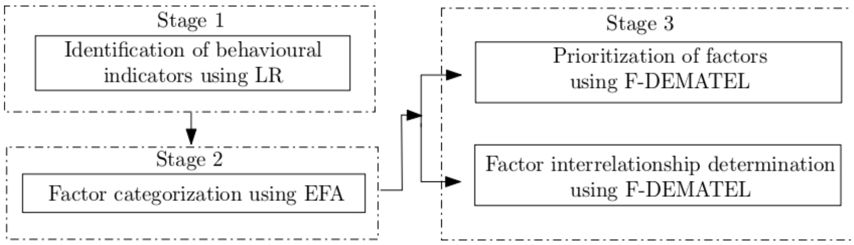

Figure 1 *Research Methodology*

4. Data Collection and Analysis

4.1 Stage 1: Identification of behavioural indicators using LR

In stage 1 of the study, which focuses on the identification of behavioural indicators using a literature review (LR) approach, a meticulous examination of existing scholarly works was undertaken (Table 1). This thorough analysis sought to identify and assemble an extensive list of behavioural indicators relevant to robo-advisory technology adoption. Twenty four behavioural indicators in all were found throughout this procedure, indicating a wide range of elements that may have an impact on people's attitudes and behaviours regarding robo-advice platforms. These indicators cover a broad range of factors, including privacy issues, perceived risk, and trust and utility perceptions about automated financial advice. The decision to use an LR-based approach was prompted by the need to leverage on existing knowledge and insights from the academic literature. Following the identification of these behavioural indicators, a crucial step was taken to validate their relevance and reliability. The Delphi technique, an organised and iterative process for reaching consensus among experts, was utilised to achieve this goal, using a panel of ten domain experts. The expert panel rigorously examined and assessed the specified indicators through a sequence of organised rounds of questioning and comments. Through this iterative procedure, the detected indicators were validated, guaranteeing that only the most trustworthy and relevant ones were kept for further research.

Table 1 *Behavioural Indicators Identified by Literature Review*

Code	Indicators	Source
TR1	I trust the portfolios recommended by the robo-advisor.	(Zhouetal., 2019)
TR2	I'm willing to share personal information with the robo-advisor.	
TR3	I trust that the robo-advisor is reliable.	
FK1	I'm well-informed about the financial market.	(Robb etal., 2012)
FK2	I'm familiar with stock trading and companies' financial status.	

FK3	I'm aware of major economic news impacting the stock market.	(Park etal., 2010)
FK4	I have extensive financial expertise.	
PE1	I find robo-advisors helpful for financial decisions.	(Venkatesh et al., 2003, 2012)
PE2	Robo-advisor would be helpful in achieving my financial goals.	
PE3	A robo-advisor would help me reach my financial goals faster.	
PE4	Using a robo-advisor would boost my financial gain.	(Moore & Benbasat, 1991)
PE5	I'm skilful in using a robo-advisor.	
PU1	Robo-advisors seem like a good tool for managing investments.	(Belanche et al., 2019)
PU2	Investing performance would be better with robo-advisors.	
PU3	Robo-advisors would boost my investment productivity.	
PU4	Robo-advisors would improve my investment effectiveness.	
HS1	Significant people believe that I should use a robo adviser.	(Venkatesh et al., 2003, 2012)
HS2	Influential people believe I should utilise a robo-advisor.	
HS3	People I value prefer that I use a robo-advisor.	(Moore & Benbasat, 1991
HS4	I'm influenced by my peers who use robo-advisors.	
AA1	I think AI will raise living standards.	(Parasuraman, 2000)
AA2	I'd like to test out goods and services that make use of AI.	
AA3	I consider AI to be mature and not to commit grave errors.	
AA4	I trust AI technology to handle complex tasks effectively.	

4.2 Stage 2: Factor categorization using EFA

EFA, a methodology that breaks down a vast number of observable indicators into smaller representative variables, marked the beginning of the second stage. In the EFA procedure, varimax rotation and principal component analysis were applied. The requirement for minimal factor loading was set at 0.40. In order to guarantee suitable levels of clarification, an assessment was conducted on the commonality of the scale that denotes the extent of variation in every dimension. Every communality topped 0.50, according to the data. Using Bartlett's Test of Sphericity, the overall significance of the correlation matrix was assessed, showing significant results ($\chi 2 = 5635.615$, $p < 0.001$), indicating it was fit for factor analysis. The Kaiser–Meyer–Olkin measure of sampling adequacy (MSA) was 0.922, confirming the data's appropriateness for this analysis (Table 2).

Table 2 *KMO and Bartlett's Test*

Test	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.922
Bartlett's Test of Sphericity	
Approx. Chi-Square 5635.615	5635.615
df	276
Sig.	.000

The factor analysis produced six factors viz. trust (TR); financial knowledge (FK); performance and effort expectancy (PE); perceived usability (PU); herding and social influence (HR); and attitude towards AI (AA), accounting for 74.97 % of the data's variation (Table 3). The scree plot displays six factors with threshold eigenvalues, which correspond to factors with eigenvalues larger than one (Figure. 2).

Table 3 *Rotated Component Matrix*

Indicators	1	2	3	4	5	6
PE1	0.730					
PE2	0.742					
PE3	0.720					
PE4	0.724					
PE5	0.743					
FK1					0.748	
FK2					0.720	
FK3					0.755	
FK4					0.732	
PU1				0.766		
PU2				0.766		
PU3				0.810		
PU4				0.787		
TR1						0.809
TR2						0.811
TR3						0.811
HS1			0.763			

HS2			0.789			
HS3			0.791			
HS4			0.811			
AA1		0.821				
AA2		0.801				
AA3		0.787				
AA4		0.777				

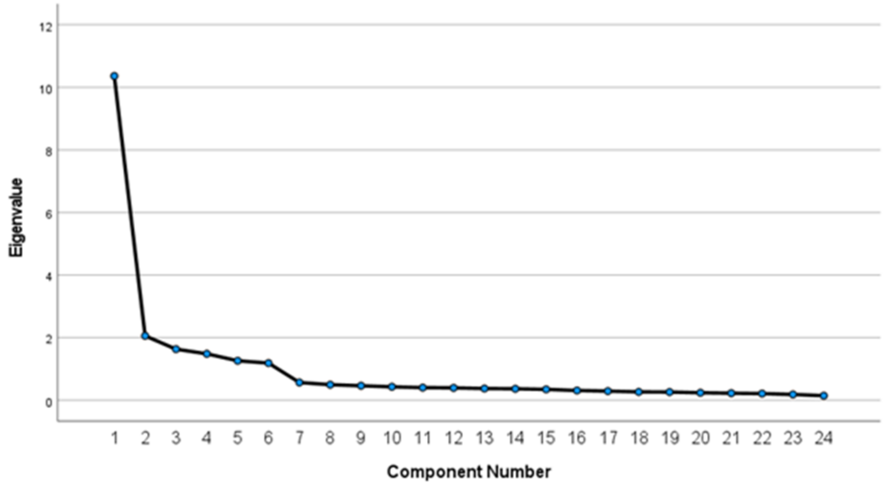

Figure 2 *Scree Plot*

4.3 Stage 3: Prioritization and Factor Interrelationship Determination using F-Dematel

The F-DEMATEL multi criteria decision making (MCDM) technique objectively examines the interrelationships between numerous criteria in a complex setting, taking into account both direct and indirect affects (Gupta and Jayant, 2021; Saraswathi, 2019). It provides a thorough approach to building and analysing a structural model of intricate relationships inside a system, ranking interdependent elements, and establishing a hierarchy of causes and effects. The fuzzy DEMATEL process involves constructing an initial direct-relation matrix using expert evaluations and incorporating fuzzy logic to handle uncertainty (Abhijith and Bijulal, 2024). Ten experts from academics and industry who have over twelve years of expertise investing in stocks are selected for data collection. Consented opinions of experts on ranking and cause-effect categorization of identified factors were then solicited through repeated iteration. The total relation matrix, which represents the overall influence of each element, is calculated by adding the direct and indirect effects after the original direct-relation matrix has been normalised to assure comparability. By analysing the total relation matrix, cause and effect factors are identified based on the sum of influences given and received. Finally, factors are ranked according to their prominence and role in the cause-effect relationship, providing a structured approach to evaluate complex interdependencies and prioritize factors effectively. Factors are ranked in descending order based on sum of row total and column total (Ri + Ci) values. They are categorized into causes or effects based on the sign of the difference between row total and column total (Ri − Ci) values: negative values indicate effects, while positive values indicate causes (Table 4).

Table 4 *Prioritization and Cause-Effect Analysis*

Factors	R_i	C_i	$R_i + C_i$	Rank	$R_i - C_i$	Attribute
HR	4.259915	3.141064	7.400979	3	1.118852	Cause
PU	3.413551	3.727888	7.141439	5	-0.31434	Effect
PE	3.302447	4.06684	7.369286	4	-0.76439	Effect
FK	4.155709	3.253902	7.409611	2	0.901808	Cause
AA	1.959305	2.901233	4.860538	6	-0.94193	Effect
TR	4.808929	3.654266	8.463195	1	1.154663	Cause

5. Results and Discussions

This section deals with various results and findings obtained out of the estimation process. The results are divided among the areas of volatility clustering, persistence, asymmetric behaviour and price interdependence and contagion effects. This study commenced with identification of 24 behavioural indicators influencing adoption of robo-advisors for financial decision making through extensive literature review. These 24 indicators are validated and categorized in to six factors namely trust (TR); financial knowledge (FK); performance and effort expectancy (PE); perceived usability (PU); herding and social influence (HR); and attitude towards AI (AA) by utilizing EFA. Factors and their underlying items identified corroborates with many earlier studies on robo-advisors (Kneller, 2017; Belanche et al., 2019; Robb et al., 2012; Moore and Benbasat, 1991). The six factors identified by EFA is then prioritized utilizing F-DEMATEL in the order of their significance on influence on robo-advisor adoption. These factors were ranked in the respective order of trust (TR); financial knowledge (FK); herding and social influence (HR); performance and effort expectancy; perceived usability (PU); and attitude towards AI (AA) (Fig. 3). Subsequently, cause and effect determination among these six factors were determined using F-DEMATEL (Fig. 4). Trust (TS); financial knowledge (FK); and herding and social influence (HR) were identified as causing leading to the effects performance and effort expectancy (PE); perceived usability (PU); and attitude towards AI (AA). Its interesting to note that factors identified as the causes were the one with significant influence on robo-advisor adoption. Trust (TR) is identified as the most affective factor in the adoption of robo-advisors (Zhou et al., 2020), as it directly impacts perceived usability (PU), attitude towards AI (AA), and performance and effort expectancy (PE). High trust in robo-advisors is crucial for users to feel confident in adopting the technology. Financial knowledge (FK) is the next significant factor (Park et al., 2016), as it enhances trust and shapes performance expectations; investors with better financial knowledge are more inclined to comprehend and trust robo-advisors. Herding and social influence (HR) also play a critical role, influencing attitudes towards AI and indirectly affecting trust and usability perceptions, as users tend to follow the behaviours and opinions of others. Performance and effort expectancy (PE) acts as an effect and is shaped by trust and financial knowledge, determining how appealing users find robo-advisors. Perceived usability (PU) is largely an effect of trust, financial knowledge, and performance expectancy. Lastly, attitude towards AI (AA) is the least influential as it is shaped by all other factors. This ranking and cause-effect analysis, highlights the importance of building trust, improving financial knowledge, and leveraging social influence to enhance the adoption of robo-advisors.

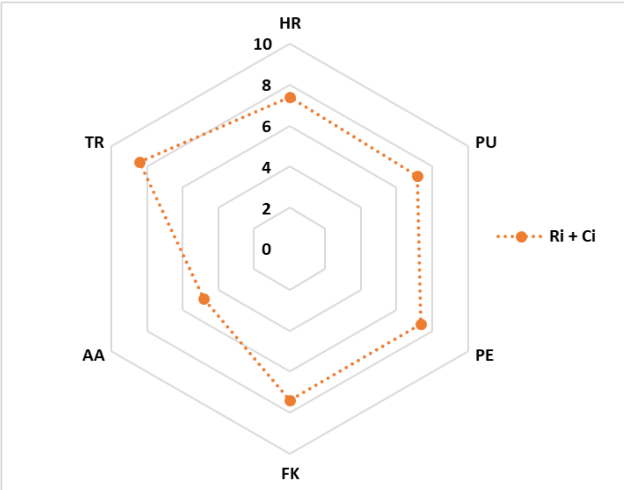

Figure 3 *Radar chart Indicating Ranks*

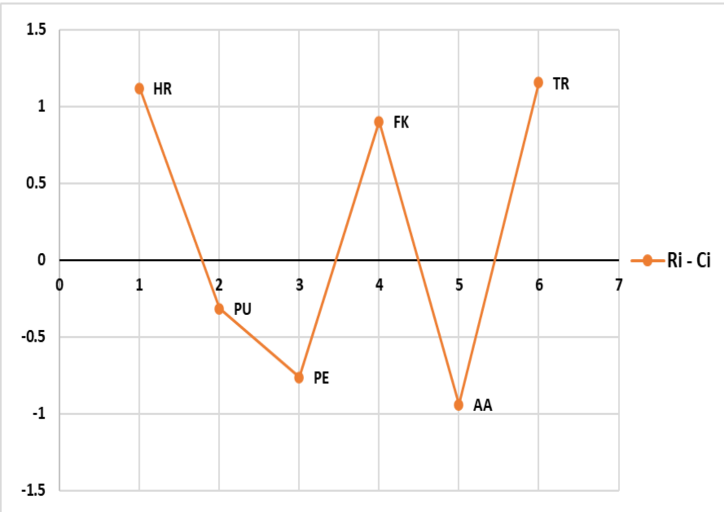

Figure 4 *Cause-Effect Diagram*

6. Conclusions and Recommendations

This study provides novel contribution by identifying, prioritizing, and determining the cause-effect relationships of behavioural factors influencing the adoption of robo-advisors. One of the key novel contributions is the identification of herding and social influence as new behavioural factors, emphasizing the impact of behavioural biases. The study underscores the critical roles of trust, financial knowledge, and herding due to social influence in shaping perceived usability, perceived expectancy, and attitudes towards robo-advisors. These findings extend existing technology adoption frameworks by incorporating new dimensions of behavioural influence, thereby enriching the theoretical landscape. Practically, the study offers valuable insights for developers and marketers of robo-advisors. Building trust in robo-advisors requires clarity about their functioning and data security. Regular security upgrades and real-time customer assistance can boost consumer confidence, but information should be adequate to minimize overburden. Enhancing financial literacy through strategies such as webinars and workshops can help, but it is critical to maintain information reliability to avoid misuse. Social proof measures, such as testimonials, can attract users, but trends must be promoted carefully to avoid market distortions. Usability should be promoted through simple designs automation, yet too much automation may limit user interest. Setting reasonable expectations can be achieved by educating people about AI's capabilities and limitations, as well as through sensible advertising. However, it is critical to counteract any adverse effects, such as over-reliance on technology and market distortions, by balancing automation with user knowledge and encouraging educated decision making. Addressing these factors strategically can increase robo-advisor acceptance and user satisfaction.

7. Limitations and Future Scope of Study

The finding's limited relevance across many areas with diverse regulatory and cultural conditions can be attributed to the sample size of 352 stock investors and their regional concentration. It's possible that some important aspects were missed even though 24 behavioural indicators were found and categorised into six groups. Furthermore, there are methodological biases due to EFA and F-DEMATEL, and the results are a temporal snapshot that may vary as time goes on. Future studies should examine additional characteristics like risk tolerance and privacy concerns, as well as more geographical areas. Additionally, the theoretical model can be evaluated using techniques like ANN and SEM. Thorough understanding can be achieved by integrating findings with other technological frameworks, analysing the regulatory changes, and investigating advancements in AI. Implications of the current work will be strengthened by addressing these constraints, providing deeper insights for financial institutions and policymakers.

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