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Investigating the role of robo advisors in investment decisions through the mediating effect of investment advice confidence

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Abstract
The impact of humanising AI-powered robo-advisors on investing behaviours is investigated in this study, which addresses anthropomorphism ideas. In this study, we investigate when trying to determine how robo-advisor anthropomorphism affects people's propensity to invest, certainty is key. We talk about the theoretical and practical ramifications of robo-advisors in marketing tactics for financial services. We use Structural Equation Modelling to look at how Rob advisor use, perceived certainty, and investment decisions are related. We use Structural Equation Modelling to look at how Robo advisor use, perceived certainty, and investment decisions are related. We used SmartPls 4 to test the model.

Keyword: Robo-advisors, Anthropomorphism, Investment decisions, Investment advice confidence, perceived certainty, structural equation modeling, SmartPLS 4, financial services marketing

Introduction

An AI-powered recommendation system that is tailored to financial services is known as a robo-advisor. By analysing clients' financial objectives, determining their risk tolerance, and overseeing their whole stock and retirement portfolios, robo-advisors provide investment advice based on algorithms developed in the field of machine learning. As more and more people use automated investment advice, the robo-advisor industry is booming. Using AI and ML to provide tailored suggestions is a major development. The growth of robo-advisory services to assist with financial planning for retirement, tax optimization, and debt management is another important trend in development. In emerging markets like India, the Robo-advisory services business is still in its early stages. Globally, the Robo-advisory segment's AUM in 2019 was $980,541 million, with an average of USD 21,421 per user in the segment ("Statistics, Market Report, 2019"). In 2014, AUM for wealth managers throughout the world was 74 trillion USD. Globally, robo-advisors will be responsible for managing approximately 10% of assets in 2020, according to BI Intelligence. That is equivalent to around $8 trillion in terms of projected value. An article titled "Business Insider Market Report" from 2019 discovered this.

The robo-advisor market is booming for a number of reasons: Affordable investment advice is in high demand among tech-savvy millennials who like internet banking. This is because most traditional money management consultants charge hefty fees and have large minimums. Customers' growing preference for digital channels hastened the transition to online financial services, such robo-advisors, in the wake of the COVID-19 epidemic. The need for affordable investment management, the surge of passive investing, and developments in artificial intelligence and machine learning will all contribute to the robo-advisor market's further expansion. Forecasts indicate that 3,270 million people will be using Robo-Advisors by the year 2028. Recently, web-based robo-advisors have gained much attention because of their potential to provide private families with low-cost professional financial advice. Because of digitalization and automation of wealth management, using state-of-the-art algorithms for portfolio management would avoid emotive decisions, hence saving time and effort (Ludden *et al*., 2015) [18]. Moving from a paper-based financial consulting process to a digital one without sacrificing trust or quality is no easy feat. According to (Jung *et al*., 2018) [16], people preferred human advisors over robo-advisors when making investments. The purpose of comparing the robo-advisor to a human advisor was to demonstrate its reliability, not to gain any further insight. Namely, trust in and adherence to investment advice by robo-advisors was higher when clients had personal contact with human advisors. At this point in time, it is unclear whether human advisors are essential or if more humanistic robo-advisors can make up for the absence of human interaction by increasing users' confidence and compliance with their investment suggestions.

Marketers in the financial sector have imbued their artificial intelligence roboadvisors with human traits, increasing the likelihood that these ads may feature anthropomorphic representations that consumers would see as social entities.

The Robo Advisory Service originated in the United States of America. According to one industry report, only 20% of investors were aware of such services, with adoption rates as low as 3%. The low level of investor acceptance of new services and platforms is one of the major concerns now being discussed when discussing the expansion of information technology into numerous areas, including financial markets. The utilisation of Robo-advisory services is low in industrialized nations, in contrast to other demographics that promote their acceptance and utilisation. Developing nations, like India, on the other hand, go through the reverse.

Prior studies have primarily concentrated on how consumers feel about robo-advisors and human financial advisors (Zhang, 2021) [25]. However, there is a lack of data regarding the persuasive power of robo-advisors, both human and machine-like, on the decision-making process related to money. We address this knowledge gap by delving into three unanswered.

Questions: Would commercials be more effective in influencing investment behaviours if they used robo-advisors that mimic human behaviour? If that's the case, how does the anthropomorphism of robo-advisors bring about their persuasive effect? Also, how might human-like robo-advisors help consumers make better financial decisions? What kinds of messages may they use?

Anthropomorphism is a process through which human characteristics are attributed to agents that are not human. It is common but not constant. (Epley, Waytz, and Cacioppo, 2007) [7], described when people anthropomorphize according to three basic underlying main psychological factors that have been presented, namely accessibility of knowledge, motivation to understand others' behaviour, and the desire for social contact. It postulates that people anthropomorphize to the extent they possess the relevant knowledge, motivation to affiliate socially, and diminished social connection with others. The factors underpin variation in anthropomorphism, organize extant research, and proffer predictions about the consequences of anthropomorphism. To what degree does the incorporation of human features into robo-advisors affect the financial habits of clients is the question this study seeks to answer. Anthropomorphism in marketing is another area that this study adds to. Expanding on earlier studies that investigated how AI anthropomorphism affected consumer behaviours like intent to buy, intention to use chatbots, and charitable giving, our research delves into the reasons and mechanisms that influence consumers' financial decision-making when it comes to AI robo-advisors.

Conceptual background

Robo-Advisor anthropomorphism

When non-human creatures or agents are believed to possess human characteristics, feelings, and intentions, this phenomenon is referred to as anthropomorphism (Guthrie, 1993; Duffy, 2003, p. 180) [11, 8]. All around the globe, you may find anthropomorphism in various artistic mediums, such as fiction, literature, and music.

One of the main factors that dictates the strength of the bond between consumers and companies is anthropomorphism, which implies that customers should interact with brands in the same manner they would with other people in their daily lives. (Aggarwal, 2004) [1]. People are more inclined to have a positive impression of things when they are linked to anthropomorphised characters, according to (Aggarwal and McGill, 2007) [2]. In finance, the usage of anthropomorphism is increasing in the creation and development of robo-advisors and financial management tools. By using anthropomorphism, a friendly voice, or even a personalized name, these digital advisors will add human-like qualities to them with the intent to instill confidence in and comfort with these tools by the user of the service. Similarly, research done by Waytz, (Cacioppo, and Epley, 2010) [23] showed that "users are more accepting and willing to follow advice provided by a financial tool when it has been anthropomorphized". Conversational robo-advisors were found to elicit higher levels of affective trust from consumers, leading them to be more receptive to investing suggestions. If the anthropomorphism hypothesis is correct (Epley, Waytz, and Cacioppo, 2007) [7], then anthropomorphising nonhuman creatures is a good way for humans to satisfy their need for social connection and exert effective control over their surroundings. In this study, we look at the connection between robo-advisors' anthropomorphism and the persuasive effect they have on investment intent, and how certainty mediates this relationship.

Perceived certainty

Perceived certainty signifies the degree of confidence a particular person has that an outcome, event, or information has a degree of reliability. It reflects the individual's confidence in their expectations, irrespective of the real uncertainty. As a result of all this, this perception may impact decision-making and make people act more decisively when they perceive the state of an outcome as being certain, even though evidence may point to the opposite. (Tversky & Kahneman, 1974) [21].

Being able to "subjectively validate the advice as a decision input" provides a sense of assurance. Source similarity and persuasion have been shown in previous research to boost perceived certainty (Wilson and Sherrell 1993) [24]. When an advisor looks a lot like the person getting advice, it might make the advice taker feel more confident, which can enhance the "feeling right" factor. Thus, consumers give favorable evaluations to similar advisors and seek and accept advice from them to keep in touch (Jiang *et al*., 2010) [15]. Reason being people are more likely to feel emotionally attached to AI if it has human-like traits. Compared to normal may provoke risk aversion, where investors would avoid investment perceived as unpredictable, even when the objective risk is low. Certainty in consumer decision-making refers to the confidence that consumers feel regarding their choices among various options. This certainty influences how quickly and decisively consumers make decisions and how satisfied they are with those decisions afterward. (Chernev & Goodman, 2015) [5]. Robo-advisors, humanlike robo-advisors have more sway because they boost the level of certainty in AI recommendations. (Baek *et al*., 2022) [3]. On the one hand, highly certain investors might take on more risk because they could feel that their investments are safe, or the markets are predictable. On the other hand, low certainty. Investment certainty is an investor's confidence in the result of his or her choices. It affects risk assessment, decision-making, and investment commitment. A high level of certainty inspires definitive and decisive actions while a low level leads to hesitation and abandonment of good opportunities. (Barber & Odean, 2001) [4]. According to (Disatnik and Steinhart, 2015), when people get fresh knowledge regarding changes in market uncertainty, their investing decisions are often influenced by their risk aversion levels.

Financial investing is inherently risky (Stockhammer and Grafl, 2010) [20], but we argue that prevention-focused customers would be more likely to participate if they hired a robo-advisor that seemed more human, rather than robotic. Supporting this line of thinking is empirical evidence that an emphasis on prevention rather than promotion elicited a more robust self- certainty aim (Leonardelli, Lakin, and Arkin, 2007) [17].

Research Methodology

Two hundred respondents are chosen, and opinion related to rob advisors and certainty in investment are collected with the help of a standard questionnaire. Bangalore is chosen as sample area as Bangalore include Tech-savvy population with high-income demographics with a lot of support for startups and innovation within the Fintech ecosystem. Convenient sampling is used as the research is exploratory in nature and specic target groups are used. It would be an appropriate choice when the research demands a quick and less costly and easy-to-operate sampling method, specifically in exploratory studies or pilot testing in which specific target groups are in focus. Structural Equation Modelling is used to investigate the relationship between Rob advisor utilisation, perceived certainty, and investment decisions. SmartPls 4 is used to test the model.

Data analysis

Table 1 summarizes the demographic profile of respondents. The demographic breakdown shows how various segments in the population perceive and use robo-advisors. The majority of the respondents were males, and this could suggest that either men are more into investment decisions, or they are simply more interested in robo-advisors. The largest group of the whole respondent base falls in the bracket of 40-49 years old, which would mean that they are probably more aggressive in the management of their investment portfolio, having achieved some level of financial stability and proximity to retirement. Many have undergraduate degrees, although a fair number of report postgraduate qualifications. The fact that many robo-advisor users are well-educated supports the idea that higher education improves understanding of financial technology. Fewer respondents make above 60,000, while almost half (44.5%) of the respondents earn between 40,000 and 60,000. Because of disposable income and a willingness to invest, middle to upper-middle-income earners are the main users of robo- advisors.

Table 1: Demographic Profile of Respondents

		Number of Respondents	Percentage
Gender	Male	123	61.5
	Female	77	38.5
	Total	200	100
Age	18-29	26	13
	30-39	35	17.5
	40-49	76	38
	50-59	29	14.5
	over 60	34	17
	Total	200	100
Education	Undergraduate	139	69.5
	Postgraduate	45	22.5
	Diploma	16	8
	Total	200	100
Income	less than 20000	24	12
	20000 to 40000	45	22.5
	40000 to 60000	89	44.5
	60000 and above	42	21
	Total	200	100

The measuring mindset and the objective of the analysis (i.e., to create predictions instead of confirmations) led to the selection of PLS-SEM over CB-SEM (covariance-based SEM), as suggested by (Hair *et al*., 2014) [12]. The PLS-SEM technique was used by examining the structural models in addition to the measurement data.

Table 2: Reliability and Validity

	Item Loading	Cronbach's alpha	Composite reliability	Average variance extracted
Robo Advisor		0.783	0.857	0.6
RBADV_1	0.776			
RBADV_2	0.795			
RBADV_3	0.815			
RBADV_4	0.707			
Perceived Certainty				

PERCER_1	0.805	0.831	0.883	0.656
PERCER_2	0.873			
PERCER_3	0.695			
PERCER_4	0.854			
Investment Decision				
INVINT_1	0.839	0.894	0.922	0.702
INVINT_2	0.814			
INVINT_3	0.826			
INVINT_4	0.862			
INVINY_5	0.847			

Measurement model

The measuring model's construct measures were evaluated for discriminant validity, convergent validity, and internal consistency reliability. To determine how reliable the constructs were, we used composite reliability and Cronbach's alpha. The table shows that the measures are highly reliable (Hair *et al.*, 2014) [12]. There is strong validity and reliability evidence for all three constructs. The internal consistency was deemed satisfactory to exceptional since the Cronbach's alpha values were more than 0.7. Overall, the composite dependability is high, as the values are more than 0.8. Good convergent validity for all constructs is shown by AVE values greater than 0.5. This indicates that the items utilized in the questionnaire were appropriate to measure the respective constructs with respect to Robo Advisors, perceived certainty, and investment decisions.

Table 3: Fornell-Larcker Criterion for discriminant Validity

	Investment Intention	Perceived Certainty	Robo Advisor
Investment Intention	0.838		
Perceived Certainty	0.263	0.81	
Robo Advisor	0.265	0.149	0.774

All three of these constructs, Investment Intention, Perceived Certainty, and Robo Advisor meet the requirements of the Fornell-Larcker test. Discriminant validity is attained in the model when each construct shows greater variance with its own indicators than with other constructs.

Table 4: HTMT assessment of discriminant validity

	Investment Intention	Perceived Certainty	Robo Advisor
Investment Intention			
Perceived Certainty	0.288		
Robo Advisor	0.309	0.168	

To determine discriminant validity, we look at how different the constructs are from one another using the Heterotrait-Monotrait (HTMT) correlation ratio. All HTMT values are lower than the cutoff of 0.85 which means that the model's constructs have strong discriminant validity. It appears that the constructs are measuring distinct underlying processes, with little to no overlap between them. (Hensler al., 2015) [13] and (Voorhees *et al.*, 2016) [22] introduced a novel construct ratio, the heterotrait-monotrait ratio (HTMT), as a measure for discriminant validity. The HTMT approach is perfect because it "offers the best balance between high detection and low arbitrary violation (i.e., false positive) rates" (Voorhees *et al.*, 2016) [22]. According to Hensler *et al.* (2015) [13] and Voorhees *et al.* (2016) [22], the HTMT ratio should be more than 0.85 to ensure discriminant validity. Table data shows that all HTMT ratios are lower than the cutoff of 0.85.

Structural model

We could determine if the path coefficients were relevant to the structural model by using the 95% bias-corrected and accelerated (BCa) bootstrap confidence intervals with 5000 re- samples. This test related to the cross-validated redundancy of the endogenous variable. (Chin, 1998) [6]. According to the standardised root mean square residual, which is a model validation index, the overall model fit was less than 0.08. The results were good (Hu and Bentler, 1999) [14].

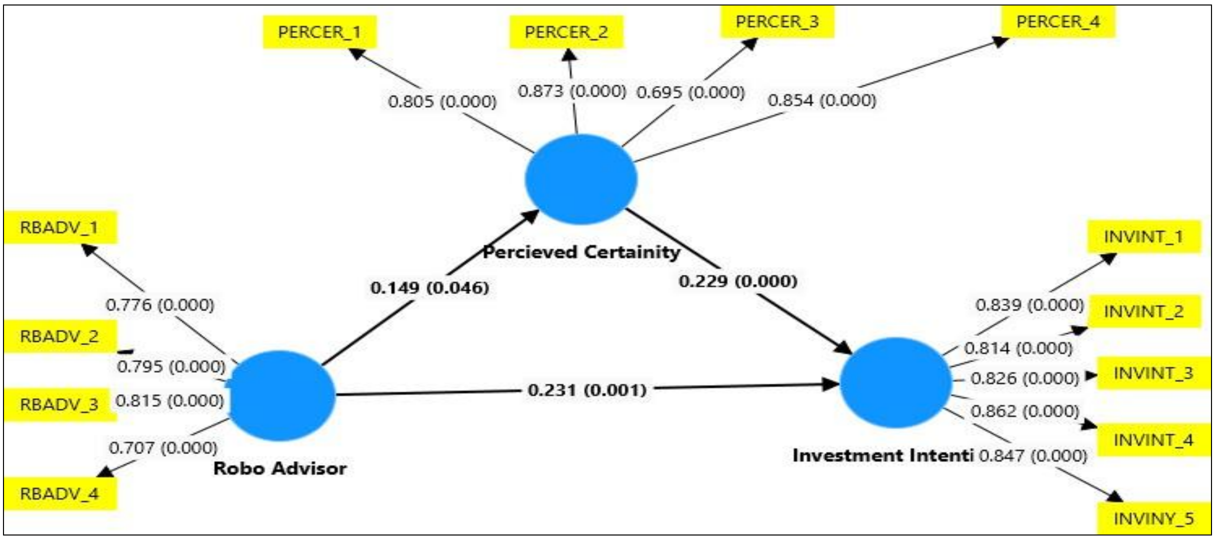

Figure 1: Structural Model

Table 5: Structural Model Estimate

	Standardised Beta Coefficient	Standard deviation	Bootstrap T-value	P values	BC 95% Bootstrap CI
Perceived Certainty -> Investment Intention	0.229	0.061	3.735	0.000	0.094,0.335
Robo Advisor -> Investment Intention	0.231	0.07	3.296	0.001	0.064, 0.348
Robo Advisor -> Perceived Certainty	0.149	0.075	1.999	0.046	0.051, 0.264

The standardized coefficient β = 0.229 expresses a positive relationship between perceived certainty and investment intention. This is statistically significant because the bootstrap t-value is 3.735 with a p-value of <.001. No value between 0.094 and 0.335 on the 95% bias-corrected bootstrap confidence range indicates that this association is not insignificant.

The beta coefficient of 0.231 indicated the Robo Advisor construct is positively related to Investment Intention. With a bootstrap t-value of 3.296 and a p-value of.001, the two variablesare strongly correlated statistically. The significance of this association is based on the fact that zero falls outside the 95% bias-corrected bootstrap confidence interval [0.064, 0.348].

The beta coefficient (β = 0.149) reflects that Robo Advisor construct is positively related to Perceived Certainty. The relationship is weaker but statistically significant since the bootstrap t-value is 1.999 with a p-value of .046. Further evidence of the significance of this relationship is provided by the 95% bias-corrected bootstrap confidence interval, which is [0.051, 0.264].

Table 6: Mediation

	Standardised Beta Coefficient	Standard deviation	T statistics	P values
Robo Advisor -> Perceived Certainty -> Investment Intention	0.034	0.02	1.97	0.047

Data are provided to test perceived certainty as a mediating variable between robo advisor and investment intention. The mediated path is represented by the beta coefficient which is estimated at 0.034. This is indicative of the magnitude of the indirect effect of Robo Advisors through Perceived Certainty on Investment Intention. A positive coefficient reflects partial mediation, such that the Robo Advisor's influence on Investment Intention is partly mediated through the increase in Perceived Certainty. With a p-value of 0.047, which is less than the significance criterion of 0.05, the mediation effect is considered significant. There is a mediating role for Perceived Certainty between Robo Advisor and Investment Intention, since the p-value is less than 0.05.

Discussion and Conclusion

The link between Perceived Certainty and Investment Intention has positive and significant values, indicating that as investors' perceived certainty grows, so does their intention to invest using robo-advisors. The correlation between the Robo Advisor concept and Investment Intention is likewise favourable and substantial. This suggests that robo-advisors' features, usability, and perceived benefits positively influence investors' intentions to use them. Finally, there is a positive and substantial association between Robo Advisor and Perceived Certainty, which suggests that using robo-advisors increases investors' perceived certainty when making investing decisions. Results show that robo-advisors and investment intent are mediated by how confident people feel in the advice they receive. According to (Epley, Waytz, and Cacioppo, 2007) [7], researchers discovered that robo-anthropomorphism advisers' distinct approach might be better understood by raising the perceived certainty level. Investors' trust in robo-advisors mitigates the effect of anthropomorphism on their financial choices, according to the study's authors.

Practical Implications

The consequences of this article for financial service are practical. Advertising plans. Consumers can also benefit from Roobo-advisors. Since they are more affordable than human consultants on matters of acquiring financial advice. Investors may seek out human interaction to alleviate their concerns and anxieties about investing. Using visualisation tools driven by Al, marketers in the financial services industry can give robo-advisors a more human appearance. This indicates that marketers utilising these robo-advisors should improve the effectiveness of their communication campaigns. Such signals stimulate a focus on prevention. From a different managerial vantage point, marketers of financial services can collect and use customer financial data to assess risks instead of advantages. Humanoid Robo-advisors can achieve this by using conversational chatbots or mobile apps to enquire about customers' present financial status and risk tolerance.

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