AN EMPIRICAL ANALYSIS OF THE FACTORS INFLUENCING THE ADOPTION OF ROBO-ADVISORY IN WEALTH MANAGEMENT

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Abstract: Advancements in digital technologies, the internet and artificial intelligence have revolutionized financial institutions in optimistic ways. These emerging technologies are transforming conventional banking institutions. Instead of having a regular broker, Robo-advisors are the latest way to get customized financial services. This paper aims to study the investor's attitude, acceptance, liking and conception toward the adoption of Robo-advisory in wealth management in Chennai, Tamilnadu. Furthermore, the focus of this work is on the perceptual characteristics of consumers as well as behavioral variables that affect their investment decisions. The work is grounded on theories like the Theory of Planned Behavior (TPB), Motivational Model and Technology Acceptance Model. The study adopted a quantitative methodology in which a survey was conducted with 300 investors who were selected using purposive sampling technique and have prior experience in using Robo-advisory in investments. The study used an independent/input variable like Perceived Usefulness, Perceived Ease of Use, Intrinsic motivation, Compatibility, Facilitating Conditions, and Self-Efficacy. The dependent/outcome variables included Attitude Towards Behavior, Behavioral Intention to Use and Actual Usage of Robo-advisory. The findings show that investors hold a positive attitude toward Robo-advisory in wealth management. The study highlights the implications of Robo-adoption adoption in wealth management.

***Keywords*:**

1. Introduction

Artificial intelligence (AI) advances have had a huge effect on different aspects of human life, and it is projected to influence multiple jobs around the world. Tourism and travel, healthcare and pharmaceuticals, industrial manufacturing and production, telecommunications, education, and other industries are all vigorously embracing artificial intelligence. The wealth management industry has been undergoing a tremendous transformation in recent years. Customers' interest in conventional wealth management firms has been eroding for many years. Demand for engaging customer experiences by goal-based strategy, as well as a desire for using emerging technologies to assist in wealth management is widely favored. Wealth management firms have recently begun designing and implementing artificial intelligence-based services to offer prompt financial advice to their customers at their convenience (Singh & Kaur, 2017). Increasingly, robots or "Robo Advisors" are used in financial advisory services. Robot technology combines the advantages of digitalization and goal-based investing for wealth management. "Robo-advisors are digital platforms that provide automated, algorithm-based financial planning services with little to no human supervision" (Ayn, 2019). "As an online financial advisory platform, Robo-advisors provide investment management services, including automated portfolio planning, automatic asset allocation, online risk assessments, account rebalancing and numerous other digital tools" (E&Y Report, 2018).

The main advantage of Robo advisors is that it eliminates the need for using a human financial advisor for wealth management. It enables customers to directly access 100% of their portfolios using the software-based application. Robo-advisory services can be accessed quickly at a cheaper cost in a transparent and unbiased manner when compared with human-based wealth advisory services. The use of Robo-advisors in asset management has resulted in significant success in recent years. A report highlights that as of November 2017, the top four Robo-advisors have successfully managed $128 billion in assets, which is more than $88 billion from that of the year 2015 (E&Y Report, 2018).

2. Review of Literature

Since Robo-advisory is a relatively recent innovation, there is a scarcity of systematic literature that illustrates the phenomenon from different perspectives. Park et al. (2016) have pointed out the paucity of studies on the subject "Robo-

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Advisory". They studied the current state of adoption of Robo-advisors in the United States and identified the practical and successful features of Robo-advisors. According to their research, the portfolio management system based on Robo-advisory technology is based is still in the early preliminary stages of growth, and there is a need for further development. They also acknowledged that there are also numerous opportunities. Fisch et al. (2017) have conducted a study to measure the efficiency of Robo-advisory based investment portfolio advice and compared the performance of Robo-advisory with human advisors. The study determines how much Robo-advisory is influenced by conflicts of interest and is an aspect to remember when it comes to a human advisory. The authors conclude that Robo-advisors are more successful than human advisors at recognizing gaps in personal risk preferences. The authors stressed that Robo-advisors are beneficial because they consider investment horizons and have a more diversified portfolio than human advisors. The risk of a Robo-advisor being influenced by biases such as socioeconomic or personal inclusion is also minimized. According to Fein (Ibid.), Robo-advisory may be a good option for small investors who are comfortable making investment decisions on digital platforms.

3. Measurement Instruments

A conceptual model was developed based on the insights obtained from different literature including the Technology Acceptance Model (Davis et al. 1989; Venkatesh & Davis, 2000), Theory of Planned Behavior (TPB) (Ajzen & Fishbein, 1980; Ajzen, 2100), Motivational Model (Vallerand, 1992). Based on the outcome of the review of the literature and theoretical frameworks, a questionnaire was designed to measure the influence of different predictor variables like Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Intrinsic motivation (IM), Compatibility (COM), Facilitating Conditions (FC) and Self-Efficacy (SE) on the outcome variables Attitude Towards Behavior (ATB), Behavioral Intention to Use (BIU) and Actual Usage of Robo-advisory.

Perceived Usefulness (PU) measures the degree to which a person believes that using a system would enhance his/her job performance (Davis et al., 1989, p. 320). Perceived Ease of Use (PEOU) is used to a degree to which a person believes that using a system would be free of efforts (Davis et al., 1989, p. 320). Intrinsic motivation (IM) refers to engaging in an activity for itself and for pleasure and satisfaction derived from participation (Vallerand 1992). According to Davis et al. (1992), Intrinsic motivation is the perception that a user will want to perform an activity for no apparent reinforcement other than the process of performing an activity per se. Compatibility (COM) is the degree to which an innovation is perceived as being consistent with the existing values, needs and past experiences of potential adopters (Moore and Benbasat, 1991). Facilitating conditions are defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Thompson et al., 1991). Self-Efficacy is the "belief in one's capabilities to organize and execute the courses of action required to manage prospective situations", or in other words, it can be said that perceived ability is the belief of a person in his or her ability to succeed in a particular situation (Bandura, 1995). Attitude Towards Behavior is an individual‘s positive or negative feelings (evaluative effect) about performing the target behavior (Fishbein and Ajzen 1975, p.216).

4. Research Methodology

This study has applied the descriptive research design method. A quantitative survey instrument was developed by the authors for data collection from the investors involved in share trading and investments (Churchill & Iacobucci, 2006).

4.1 Sample and Setting

The aim of the study was studying the impact of different factors on the adoption of Robo Advisors in Wealth Management. The sample of the study was selected using purposive sampling method. The respondents consisting of investors were personally approached and requested to take part in the study. The area of the study was limited to the Chennai Region, Tamilnadu, India. The overall sample of the study consisted of 321 investors who have better knowledge in investing and wealth management. The demographics characteristics of the investor sample of the study is presented in Table 1.

Table 1: Demographics Profile

Demographic Variable	Category	Frequency	Percent
Gender	Male	273	85.0
	Female	47	15.0
Age (years)	0 – 30	6	1.9
	31 – 40	112	34.9
	41 – 50	124	38.6
	Above 50	79	24.6
Income (Month)	Below Rs. 10000	18	6.00
	Rs.10001 - 300000	40	13.33

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Demographic Variable	Category	Frequency	Percent
	Rs.30001 – Rs. 60000	74	24.67
	Rs. 60001 – Rs. 1,00,00	50	16.67
	Above Rs. 1,00, 000	118	39.33
Education	Higher Secondary and Below	4	1.33
	Undergraduate	88	29.33
	Postgraduate	182	60.67
	Professional	26	8.67

From Table 1, it is inferred that Male investors made up 85.0 per cent of the investor pool, while female investors made up just 19.6 per cent. The gender profile represents the traditional Indian situation, with men accounting for most investors. Most investors were between the ages of 41 and 50 years (38.6%), followed by 31 to 40 years (34.9%), and above 50 years (24.6%). Most investor respondents earned over one lakh rupees per month 10 and 25 lakhs a year (39.33 %). This was followed by investors with monthly income between Rs.30001 – Rs. 60000 (24.67%), Rs. 60001 – Rs. 1,00,00 per month (16.67%) and Rs.10001 - 300000 (13.33%) per month. Interestingly the majority of the study investors have Postgraduate (60.67%) and undergraduate (29.33%) qualification. 8.67 per cent of respondents have professional qualifications.

4.2 Research Objectives

The objectives of the study are listed below;

- To study the investors' awareness of Robo-advisory in wealth management.
- To study the investors' attitude towards Robo-advisory in wealth management.
- To examine the influence of attitude towards Robo-advisory on the behavioral intention to use.
- To study the extent of usage of Robo-advisory in wealth management

5. Results and Discussion

5.1 Descriptive Statistical Analysis and Reliability Analysis

Descriptive statistical measures are used to represent the data using parameters like mean, standard deviation (SD), kurtosis and skewness. It is important to verify the normality of the quantitative outcome measure in order to present accurate descriptive data as well as use the appropriate statistical tests. Skewness is a metric for measuring the presence or absence of symmetry in the dataset. Skewness between -1 and 1 is an acceptable level for normality. Kurtosis is a test of whether the results are peaked or flat compared to a normal distribution. The value of kurtosis between -1 to 1 is an acceptable value for normality (Joanes and Gill 1998).

Table 2: Descriptive Statistics (N=300)

Variables	No. of Items	Mean	Std. Deviation	Skewness	Kurtosis	Cronbach's Alpha
Perceived Usefulness	3	3.86	0.76	-0.44	0.89	0.930
Perceived Ease of Use	6	3.85	0.83	-0.51	0.26	0.954
Attitude Towards Behaviour	6	3.83	0.74	-0.68	0.98	0.964
Intrinsic motivation	7	3.80	0.95	-0.50	-0.31	0.970
Compatibility	3	3.85	0.92	-0.72	0.41	0.919
Facilitating Conditions	8	3.84	0.86	-0.59	0.40	0.947
Self-Efficacy	9	3.87	0.78	-0.63	0.96	0.966
Behavioural Intention to Use	6	3.79	0.84	-0.54	0.86	0.926
Actual Usage of Robo-advisory	4	3.79	0.93	-0.83	0.66	0.922

The values of both Skewness and Kurtosis for the measures were in the range of -1 to +1, suggesting a normal distribution.

Self-Efficacy with a mean value (M) of 3.87 and standard deviation (SD) of 0.78 was the highest-rated variable, followed by Perceived Usefulness (M=3.86, SD=0.76),

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Perceived Ease Of Use (M=3.85, SD=0.83), Compatibility (M=3.85, SD=0.92), Facilitating Conditions (M=3.84, SD=0.86) and Intrinsic motivation (M=3.8, SD=0.95), The outcome variables like Attitude Towards Behaviour (M=3.83, SD=0.74), Behavioural Intention to Use (M=3.79, SD=0.84), Actual Usage of Robo-advisory (M=3.79, SD=0.93) were rated moderately. The values of skewness and kurtosis are within the prescribed limits, indicating that the measures satisfy normality assumptions. The reliability of the variables was assessed by examining Cronbach's alpha. The alpha values for all the variables are above the acceptable level of 0.7. The reliability for all the measures varies between 0.919 and 0.970 well above the acceptable limit of 0.70 (Nunnally 1978).

5.2 Hypothesis Testing

To test the hypothesized model, the following synthesis were framed in this study:

Hypothesis 1: Perceived usefulness has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management.
Hypothesis 2: Perceived ease of use has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management.
Hypothesis 3: Intrinsic Motivation has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management.
Hypothesis 4: Compatibility has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management.
Hypothesis 5: Facilitating conditions have a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management.
Hypothesis 6: Self-efficacy has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management.
Hypothesis 7: Attitude towards Behavior in using Robo-advisory is positively related to behavioral intention to use Robo-advisory in wealth management. (Nunnally 1978).

Hypothesis 8: Behavioral intention to use is positively related to the actual usage of Robo- advisory in wealth management.

The hypothesized model was tested using AMOS 21.0.

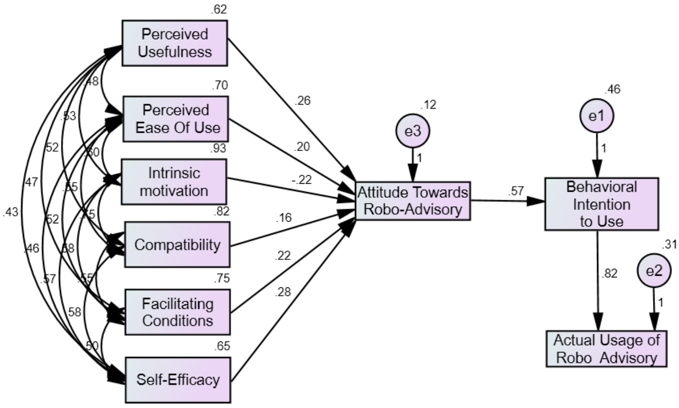

Figure 1: SEM Model

The standardized regression estimates of the SEM analysis are shown in Table 3. All the predictor's variables like Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Intrinsic motivation (IM), Compatibility (COMP), Facilitating Conditions (FC) and Self-Efficacy (SE) have a significant and positive impact on the outcome variable Attitude Towards Behavior (ATB). Similarly, Attitude Towards Behavior (ATB), in turn, has a significant impact on Behavioral intention to use (BIU). Finally, Behavioral intention to use (BIU) has a significant impact on the Actual usage of Robo-advisory (AURA) in wealth management.

Table 3: Standardised Regression Estimates

Outcome Variable		Predictor Variable	Estimate	S.E.	C.R.	P-value
ATB	<---	PU	0.28	0.04	6.17	***
ATB	<---	SE	0.31	0.05	6.29	***
ATB	<---	PEOU	0.22	0.04	4.65	***
ATB	<---	FC	0.25	0.04	5.58	***
ATB	<---	IM	-0.29	0.04	-5.00	***
ATB	<---	COMP	0.20	0.05	3.27	0.00
BIU	<---	ATB	0.53	0.05	10.74	***
AURA	<---	BIU	0.76	0.04	20.26	***

*** - Significant at 0.01 level

Table 4 shows the goodness of fit indices values for the hypothesized model. The goodness of fit measures how well the model fits the set of observations. From the table, it is obvious that the fit indices values obtained for the measurement model within the specified range of the recommended values. This, it is inferred that the model can be considered as a good fit model. The values obtained for the indices like GFI (Goodness of Fit Index) (Hair et al 2006), AGFI (Adjusted Goodness of Fit Index) (Hair et al 2006), CFI(Comparative Fit Index) (Hu & Bentler 1999) are greater than the recommended value of 0.9 which shows that the model is perfectly fit (Daire et al. 2008; Hu and Bentler, 1999). RMSEA (Root Mean Square Error of Approximation) value was less than the recommended value of 0.09 (Hair et al 2006) suggesting that the model is perfectly fit. Overall values

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for model fit indices and measures obtained in the study are at an acceptable level. Hence, it can be concluded that the SEM model is perfectly fit for measurements and drawing conclusions

Table 4: Goodness of Fit Indices

Indices	Suggested value	Obtained Value
Chi-square value	-	62.925
DF	-	13
Chi-square value/DF (CMIN)	< 5.00 (Hair et al., 1998)	4.84
GFI	> 0.90 (Hu and Bentler, 1999)	0.958
AGFI	> 0.90 (Hair et al. 2006)	0.901
NFI	> 0.90 (Hu and Bentler, 1999)	0.974
CFI	> 0.90 (Daire et al., 2008)	0.979
RMR	< 0.08 (Hair et al. 2006)	0.048
RMSEA	< 0.09 (Hair et al. 2006)	0.088

5.3 Testing of Hypothesis

The hypothesis is tested based on the multiple regression analysis performed using SEM analysis (Table 3).

Hypothesis 1: Perceived usefulness has a significant impact on Attitude towards Behavior in using Robo - advisory in wealth management.

From the results of standardized regression estimates (Table 3), it is inferred that Perceived usefulness (PU) has a significant impact (R=0.28) on attitude towards Behavior (ATB) in using Robo-advisory in wealth management. The level of significance was 0.01 ($p<0.01$). Thus, the hypothesis that "Perceived usefulness has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management" was accepted.

Hypothesis 2: Perceived ease of use has a significant impact on Attitude towards Behavior in using Robo – advisory in wealth management.

From the results of standardized regression estimates (Table 3), it is inferred that Perceived ease of use (PEOU) has a significant impact (R=0.22) on attitude towards Behavior (ATB) in using Robo-advisory in wealth management. The level of significance was 0.01 ($p<0.01$). Thus, the hypothesis that "Perceived ease of use has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management" was accepted.

Hypothesis 3: Intrinsic Motivation has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management.

From the results of standardized regression estimates (Table 3), it is inferred that Intrinsic Motivation (IM) has a negatively significant impact (R=0.29) on attitude towards Behavior (ATB) in using Robo-advisory in wealth management. The level of significance was 0.01 ($p<0.01$). Thus, the hypothesis that "Intrinsic Motivation use has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management" was accepted

Hypothesis 4: Compatibility has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management.

From the results of standardized regression estimates (Table 3), it is inferred that Compatibility (COMP) has a significant impact (R=0.20) on attitude towards Behavior (ATB) in using Robo-advisory in wealth management. The level of significance was 0.01 ($p<0.01$). Thus, the hypothesis that "Compatibility use has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management" was accepted.

Hypothesis 5: Facilitating conditions have a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management.

From the results of standardized regression estimates (Table 3), it is inferred that Facilitating conditions (FC) have a significant impact (R=0.25) on attitude towards Behavior (ATB) in using Robo-advisory in wealth management. The level of significance was 0.01 ($p<0.01$). Thus, the hypothesis that "Facilitating conditions have a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management" was accepted.

Hypothesis 6: Self-efficacy has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management.

From the results of standardized regression estimates (Table 3), it is inferred that Self-efficacy (SE) has a significant impact (R=0.31) on attitude towards Behavior (ATB) in using Robo-advisory in wealth management. The level of significance was 0.01 ($p<0.01$). Thus, the hypothesis that "Self-efficacy has a significant impact on Attitude towards Behavior in using Robo-advisory in wealth management" was accepted.

Hypothesis 7: Attitude towards Behavior in using Robo-advisory is positively related to Behavioral intention to use Robo-advisory in wealth management.

From the results of standardized regression estimates (Table 3), it is inferred that Attitude towards Behavior (ATB) has a significant impact (R=0.53) on Behavioral intention to use (BIU) Robo-advisory in wealth management. The level of significance was 0.01 ($p<0.01$). Thus, the hypothesis that "Attitude towards Behavior in using Robo-advisory is

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positively related to Behavioral intention to use Robo-advisory in wealth management" was accepted.

Hypothesis 8: Behavioral intention to use is positively related to the actual usage of Robo - advisory in wealth management.

From the results of standardized regression estimates (Table 3), it is inferred that Behavioral intention to use (BIU) has a significant impact (R=0.76) on the Actual usage of Robo – advisory (AURA) in wealth management. The level of significance was 0.01 ($p<0.01$). Thus, the hypothesis that "Behavioral intention to use is positively related with the actual usage of Robo - advisory in wealth management" was accepted.

6. Major Findings

The study analyzed the factors influencing the attitude of investors toward the usage of Robo-advisory in wealth management. 300 investors from the city of Chennai, Tamilnadu, India were selected in this study. A questionnaire was designed to collect the quantitative responses from the participants to gauge their attitude toward different variables like Perceived Usefulness, Perceived Ease of Use, Intrinsic motivation, Compatibility, Facilitating Conditions, Self-Efficacy, Attitude Towards Behavior, Behavioral Intention to Use and Actual Usage of Robo-advisory. The study also assessed the impact of different variables (PU, SE, PEOU, FC, IM and COMP) on the Attitude Towards Behavior in using Robo-advisory in wealth management. Further, the impact of Attitude Towards Behavior in using Robo-advisory in wealth management on the Behavioral Intention to Use and the impact of Behavioral Intention to Use on Actual Usage of Robo-advisory was also measured.

Consistent with the findings of other studies (Epperson et al. 2015; Hohenberger et al. 2019; Pradhan & Wang, 2020), this study also found that the participants have a positive attitude towards Robo-advisory in wealth management. Self-Efficacy, Perceived Usefulness, Compatibility and Perceived Ease of Use related to Robo-advisory were the top-rated factors. However, the study found that respondents have negative intrinsic motivation toward using Robo-advisory in wealth management.

7. Implications

The findings of the study provide evidence on the enabling factors to Robo-advisory adoption in investments and wealth management.

This study contributes to ongoing research studies on Robo-advisory in wealth management by addressing questions about whether, and why decide to use or not use Robo-advisory service. The empirical evidence has successfully predicted the influence of different factors on the adoption of Robo-advisory in wealth management.

8. Limitation and Future Research

This study has certain limitations. The study involved a limited number of investors from Chennai, Tamilnadu. The respondents were drawn Though the respondents were selected randomly, and the sample size was 300. Also, the study did not consider the influence of factors like risk and trust in adopting Robo-advisory in wealth management. Thus, future studies may consider involving more larger sample sizes distributed across different regions. The influencing role of trust and risk could be evaluated empirically to strengthen the findings of the study

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