

From Brokers to Algorithms: Hybrid Approach of Machine Learning & Structural Equation Modelling in Portfolio Construction among Retail Investors

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Abstract

Background: Retail investors in India often invest their personal savings into the stock markets using traditional, full-service brokerages, discount brokers, and online brokers to manage their assets, make investments for their gain, and execute trades. These investors are not trained professionals who look to enhance personal earnings through their investments.

Objectives: The paper aims to examine the impact of Robo Advisory platform services in investment management leading to customer satisfaction using modern portfolio theory.

Methodology: The primary responses were collected from 384 Investors residing in Bangalore, Chennai & Hyderabad using the Cluster Sampling method through Survey Questionnaire. Aesthetics, security, ease of use, user experience, and e-satisfaction are the broader variables considered for the study. JAMOVİ & JASP software was used to examine the hypothesis through Simple Percentage Analysis, Structural Equation Modelling and Machine Learning.

Key Findings: User experience, Security, and Ease of Use are the key factors influencing investors to use Robo-services for their investment management. It can be concluded that efficiency is the most important and influencing variable for the users to rely on and trust the machine compared to the conventional method of approaching brokers for their wealth or investment management.

Implications/Significance: The robo-advisory platforms create an investing portfolio for the customer using complex algorithms taking into account several elements, including the client's risk tolerance, investing objectives, and market conditions using principles of diversification to construct portfolios.

Keywords: Robo-Advisory, Investments, Technology, service quality, and E-Customer Satisfaction

Introduction

In recent times, India has placed a lot of emphasis on financial inclusion. People's fear of technology decreased and their ability to use new technologies improved as the nation transitioned to digital payments, particularly UPI, which ultimately raised the financial inclusion rate (Huynh-The et al., 2023). Investors gained more independence beyond the features offered by their mobile banking apps, especially the younger generation became more actively involved in managing their funds, which were previously thought to be unreachable without visiting banks or ATMs (Chandani et al., 2021). Increased accessibility to information about investment alternatives contributed to financial inclusion by boosting investors' self-assurance in their ability to profit from capital markets directly, bypassing intermediaries. Financial inclusion programs, user-friendly trading apps, loosened Know Your Customers (KYC) regulations, and millennials' increasing risk appetite are the key factors influencing the rise in retail investing in stock markets (Rao & Lakshmi, 2024).

Conventional brokers generally impose greater service costs, which have a substantial impact (Chakraborty et al., 2023) on investment results over time because these intermediaries require a certain amount as seed money before allowing new investors to start trading, it can occasionally be difficult for them to enter the market (Oehler et al., 2022). Online investment management platforms firms known as "robo-advisors" use mathematical algorithms to offer financial advice with little to no human involvement. They manage and distribute client assets as efficiently as possible by using their algorithms (D'Acunto & Rossi, 2021). It is a digital software that has emerged as a promising solution in the domain of Fintech, providing financial services to the investors applying advanced technology depending on their goal, risk tolerance, expected returns, and market risks as the significant factors. Possessing financial competence aids in setting up customers for long-term financial sustainability. Nevertheless, prior research has only examined financial aptitude inside a financial framework. Customers who have access to a computer at home, are actively interested in financial services and have made general online purchases have all been known to find this

distribution channel easy to use (Nourallah, 2023). Betterment was the first robo-advisory platform (Vyas & Prasad, 2023) tested in 2008 and launched in New York to rebalance assets (Bhatia et al., 2021) focused primarily on managing buy-and-hold investment strategies through the online user interface to ensure optimal portfolios for Socially Responsible Investing (SRI). Therefore, the research questions framed to explore answers during the study are as below;

RQ₁: "Can retail investors consider robo-advisory platforms for their investment management?"

RQ₂: "Are the customers (retail investors) satisfied using Robo-advisors in Investment management?"

The previous literature contributions on Robo-advisory in developing nations have shed light on raising investor awareness and their perceptions of robo-advisory services, application of robo-advisory in banking and other service sectors, but they haven't tested for E-Satisfaction integrated with technology as an interdisciplinary study, thus confirming the research gap (Nain & Rajan, 2023). Therefore, the framed research questions aimed at investigating the E- Satisfaction in using the Robo-advisory platforms (Dutta et al., 2020) for investment management among retail investors residing in Metropolitan Cities from the Southern States of India.

Review of Literature

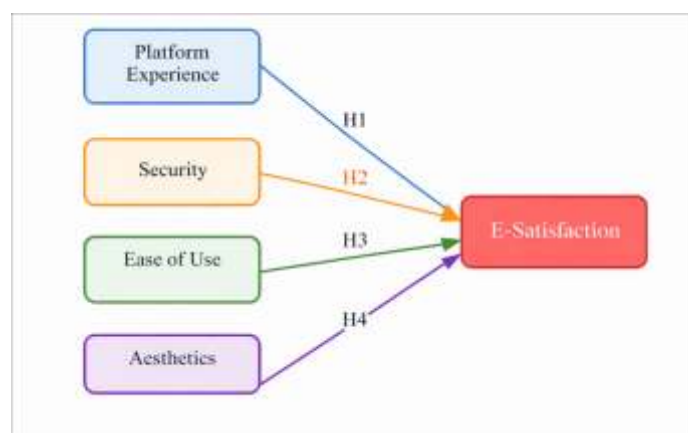
Theory of Planned Behaviour (TPB) was applied to anticipate a person's intention to invest in the stock market to investing intentions where the investor's behavior, attitude, subjective norms, and perceived behavioral control acting as influences their investment decision-making ability (Akhtar & Das, 2019). Motivational Model Theory provides a unique vantage point to observe how people manage their finances by adopting techniques that are supported by evidence for maximizing more autonomous incentives and resolving autonomous motivations that may help promote financial literacy and wellbeing (Liu et al., 2021). Robo-advisory platforms are one of the emerging disruptive technologies applied in asset and wealth management (Rahim et al., 2021) as they are automated investment platforms using quantitative algorithms to manage investors' portfolios accessed via

Internet (Kobets et al., 2022). The degree to which a customer is satisfied with the perceived performance in relation to expectations while using the platform (Eyvazpour et al., 2021).

Conceptual Development

Modern Portfolio Theory (MPT), a useful technique for choosing investments that will optimise total returns while maintaining a manageable degree of risk. Building an investment portfolio using this mathematical approach maximises the expected return for the total amount of risk. Figure 1 illustrates Platform experience, Security, Aesthetics, Ease of Use are the key dimensions (Metlo et.al., 2021) of the Robo-Advisory Platform that influences in leading to e-satisfaction when investors use these platforms to avail the services of Investment Management.

Figure 1: Proposed Research Model in Robo Advisory Platform



The experience of the platform by the user is a very significant factor among the robo-advisory platforms that offer investment management services to the end users. They offer seamless services to the investors who have limited financial knowledge or don't prefer taking the help of professional brokers.

Objective

The paper aims to examine the impact of Robo Advisory platform services in investment management leading to customer satisfaction using modern portfolio theory and to explore the key factors influencing the satisfaction.

Hypothesis

Personalization is the key feature that helps in customizing

the preferences and requirements of the users with transparency and real-time performance tracking which is more cost-effective and improves efficiency (Zhang et al., 2021). When handling sensitive information, such as personal and financial data, algorithms play a critical part in these platforms' algorithmic security to protect their clients by preventing unauthorized access (Chou et al., 2023). These platforms are extremely convenient to use by clients and simplify the investment process for investors by automating the investment recommendation process. The user interface is completely designed (Tao et al., 2021) with suitable labels and sections making it easier for the investors to extract information, generate reports (Nazari-Shirkouhi et al., 2023). The perceived end-user experience and their engagement in terms of interactions with the platform contribute significantly while assessing the aesthetics through visual design (Sabir et al., 2023) as these create a lasting impression improving the readability and clarity. Creative and real-time interactive dashboards offer pleasing visualization among investors and are designed with user-friendly icons to symbolize various features, and investment categories from pertinent pictures and illustrations creating exceptional visuals (Papadimitri et al., 2021).

H1: User experience of the platform has a positive influence on the E-Satisfaction of the investors while using the robo-advisory platforms.

H2: Security of the platform has a positive influence on the E-Satisfaction of the investors while using the robo-advisory platforms.

H3: Ease of Use of the platform has a positive influence on the E-Satisfaction of the investors while using the robo-advisory platforms.

H4: Perceived Aesthetics of the platform has a positive influence on the E-Satisfaction of the investors while using the robo-advisory platforms.

Methodology

The current research followed a deductive approach on the existing theories aimed at measuring E-customer satisfaction in using the Robo-advisory services among the retail investors. Each construct consists of four items measuring the latent dependent variable that was adapted

and refined to embrace the proposed study. The variables of 20 items were subjected to a reliability study. The questionnaire's satisfactory reliability was shown by the Cronbach's alpha ($N = 384$, $= 0.874 > 0.70$, (Hayes & Coutts, 2020), which also supported the high and excellent ($\alpha \geq 0.9$) dependability of the items.

Data Collection

Primary information was collected employing a Survey questionnaire (Smid et al., 2020) consisting of Part -A with demographic information of the respondents and Part-B of the various constructs on a five-point Likert scale (Schrum et al., 2020) anchored at “1 = Strongly Disagree” to “5 = Strongly Agree”. The demographic details of the respondents were based on the variables, gender, age group, occupation, educational background, and marital status.

The sampling framework involves all the metropolitan cities situated in the southern states of India. The urban population of the shortlisted metropolitan cities, Bangalore

(11,750,000), Chennai (11,933,000), and Hyderabad (10,584,000) were sourced (CensusIndia.gov.in) based on the predicted population as of January 2025. The total population collectively from these metropolitan cities resulted in 3,42,67,000. The selected metropolitan areas have developed into the most sought-after technical hubs because they are highly populated, have improved infrastructure and service facilities, and offer a growing number of work opportunities (Tiberius et al., 2022). The researchers ensured the circulation of 450 Self-Administered Questionnaires through Google Forms to collect the responses from the retail investors from the chosen cities. However, only 384 fully completed replies were obtained, showing that the sample size from the Cluster Sampling Method was adequate for further data analysis (Zsido et al., 2020). Table 1 illustrates the demographic profile of the respondents considered in the study.

Table 1: Demographic Profile Summary of Respondents

Demographic Grouping	Variables	Percentage
Gender	Male	78%
	Female	22%
Age Group	21 – 30 years	74%
	31 – 40 years	26%
Occupation	Salaried	85%
	Students	15%
Marital Status	Married	25%
	Single	75%
Source: Authors' compilation		

JAMOVI and JASP software were deployed to validated the hypothesis through Simple Percentage Analysis and Structural Equation Modelling. One of the straightforward statistical programs used for data analysis, very user-friendly interface and open-source platform with easy accessibility. Covariance-based Structural Equation Modelling (CB-SEM) was employed to analyse the conceptualized research model. It is regarded as one of the most sought-after tools that make it easier to test existing theories and confirm them based on the research objective and are also appropriate given the study's lower sample size (Dash & Paul, 2021).

Gradient boosting method of regression from machine learning was deployed to examine the robustness of the predicted model as they apply experts' decision tree before obtaining the results. It is a very powerful and widely applied machine learning algorithm under the supervised mechanism which combines the predictions of both weak and strong learners by splitting the data into test and training sets.

Results and Discussions

Common method bias (CMB) occurs when responses systematically differ as a result of the employment of a standard scaling methodology on measurements collected

from a single data source (Kock et al., 2021). The presence of Common-method variance (CMV) in the data was statistically tested using Harman's single factor test through unrotated Factor Analysis performed in SPSS. However, the first factor alone contributed only 38.38% of the total variance, which is much less than the suggested 50% variance explanation threshold (Beauvais et al., 2021) thus confirming the absence of standard method bias in the data. Generally, if the VIF is greater than 4 or the tolerance is lower than 0.25, multicollinearity may be present, and further research is necessary Significant multicollinearity that requires correction exists when the VIF is more than 10 or the tolerance is lower than 0.1. The Variance Inflation Factors (VIFs) were within the accepted threshold of less than 3 (Sarstedt et al., 2021) confirming the absence of multicollinearity.

Measurement Model Evaluation

Model fit was assessed using the goodness-of-fit index (GFI), the adjusted goodness-of-fit index (AGFI), the normed fit index (NFI), the comparative fit index (CFI), Normed Chi Squares, and Root Mean Square Error of Approximation (RMSEA). (Byrne, 2013) recommended a good model fit should be achieved with GFI, AGFI, and NFI higher than 0.9, CFI higher than 0.93, and RMSEA lower than 0.06. Then, the construct validity, convergent, and discriminant validity were assessed using Average Variance Extract (AVE) and Maximum Shared Variance (MSV) methods following guidelines (Chalwe et al., 2023). Additionally, the construct reliability was assessed using Cronbach's alpha and Composite Reliability (CR) (Alshurideh et al., 2023). The summary of the measurement model is described in Table 2.

Table 2: Measurement Model Summary

Construct	Items	Loadings	Cronbach α	AVE	CR	MSV
Platform Experience	PE1	0.763	0.887	0.668	0.855	0.55
	PE2	0.828				
	PE3	0.834				
	PE4	0.836				
Security	SE1	0.814	0.891	0.673	0.864	0.52
	SE2	0.804				
	SE3	0.844				
	SE4	0.822				
Aesthetics	AE1	0.721	0.793	0.490	0.658	0.57
	AE2	0.700				
	AE3	0.685				
	AE4	0.696				
Ease of Use	EU2	0.863	0.871	0.701	0.882	0.62
	EU3	0.761				
	EU4	0.875				
E-Satisfaction	ES1	0.806	0.886	0.665	0.859	0.54
	ES2	0.859				
	ES3	0.744				
	ES4	0.859				

Source: Author's Compilation

Cronbach's Alpha and Construct Reliability (CR) values are above the suggested values (0.7) for all factors, indicating good reliability (Bell et al., 2023). Measured variables have high factor loadings to the corresponding factors (greater than 0.7), and all factors have Average

Variance extracted (AVE) values being higher than 0.5, & MSV < AVE, CR, indicating good convergent validity (Cheung et al., 2023). However, one of the items measuring ease of use (EU1) was dropped as it didn't meet the minimum requirement of 0.60 factor loadings from CFA.

Table 3: Discriminant Validity – HTMT Criterion

Constructs	PEF	SEF	EUF	AEF	ESF
PEF	1.00				
SEF	0.230	1.00			
EUF	0.650	0.277	1.00		
AEF	0.238	0.041	0.228	1.00	
ESF	0.576	0.337	0.584	0.210	1.00

Source: Authors' Compilation

Table 3 reflects the discriminant validity of the variables platform experience (PEF), Security (SEF), Aesthetics (AEF), Ease of Use (EUF), and E-Satisfaction (ESF) of the constructs, which are much below the threshold values of 0.85.

Structural Model Evaluation

A path coefficient indicates the direct effect of a variable assumed to be a cause on another variable assumed to be an effect. The standardized coefficients (β), Critical ratios, and “values between the indicators and the constructs (Chiang & Trimi, 2020). Aesthetics explains only 6 %, system ease of use 35 %, Security 16 %, and platform user experience explains 29 % variance towards the E-Satisfaction among the investors availing the services.

Fig 2: Structural Model. (Source: Output from JAMOVI)

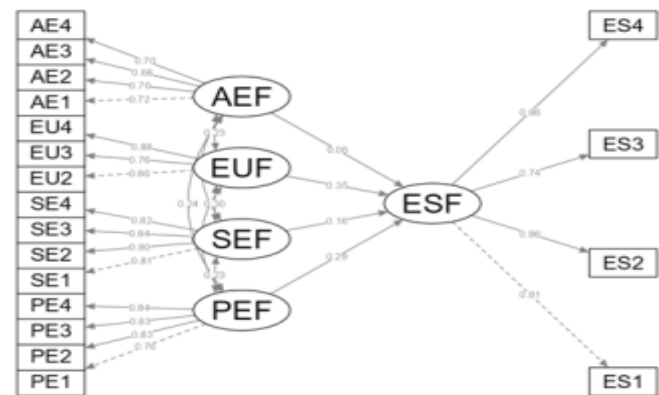


Figure 2 describes that Ease of Use is the most influencing path in determining E-satisfaction among the users. The path coefficient is interpreted as expressing the size of a relationship between two latent constructs as illustrated in Table 4.

Table 4: Path Analysis Results

Relationship	Beta (β)	z-Value	p-value	Results
Platform Experience → E-Satisfaction	0.293	4.46	<0.001**	Supported H1
Security → E-Satisfaction	0.160	3.30	<0.001**	Supported H2
Aesthetics → E-Satisfaction	0.061	1.22	0.223	Not Supported H4
Ease of Use → E-Satisfaction	0.351	5.22	<0.001**	Supported H3
Fit Indices: $\chi^2/df = 2.698$; TLI = 0.989 ; GFI = 0.905 ; AGFI = 0.978 ; CFI = 0.991 ; RMSEA = 0.025 , SRMR = 0.027 . R² = 0.440** Significant at 1%.				
Source: Authors' Compilation				

There is a positive influence of platform user experience on e-satisfaction ($\beta = 0.293$, $p < 0.001$). Security has a positive influence on e-satisfaction ($\beta = 0.160$, $p < 0.001$). Ease of Use has a positive influence (Rajaobelina et al., 2021) on e-satisfaction ($\beta = 0.351$, $p < 0.001$). However, the perceived aesthetics of the platform has no significant influence on the e-satisfaction ($\beta = 0.061$, $p > 0.05$) among the investors. The findings of the study demonstrate that ease of use is the most influencing factor in determining the e-satisfaction

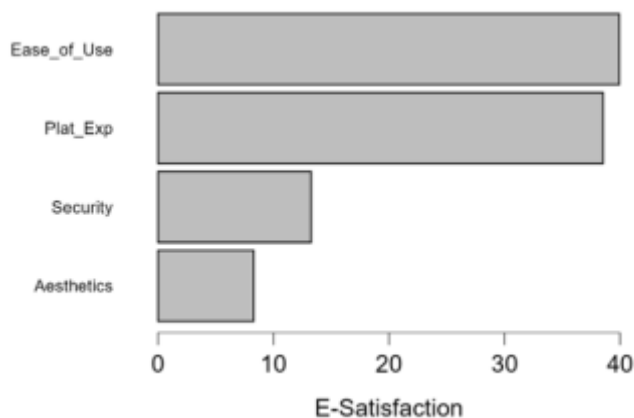
among the retail investors using the robo-advisory service platforms for their investment management. However, the gradient boosting regression-based machine learning technique was used to assess the anticipated model's resilience. Table 5 illustrates the model performance metrics through Mean absolute percentage error (MAPE), Root Mean Square Error (RMSE), Mean Squared Error (MSE), R², and Mean absolute error (MAE).

Table 5: Gradient Boosting Model Performance Metrics

Construct	Relative Influence	MSE	RMSE	MAE	MAPE	R ²
Ease of Use	39.93	0.566	2.471	1.913	16.58	0.508
Platform Exp	38.53					
Security	13.25					
Aesthetics	8.28					
Source: Authors' Compilation						

Overall, these metrics suggest a model with moderate predictive performance from gradient boosting method. The R² value of 0.508 indicates limited explanatory power, while the error metrics (MSE, RMSE, MAE) suggest notable prediction errors. The MAPE of 16.58% confirms that there's room for improvement in the model's accuracy. The relative influence plot illustrated in figure 3 offers a visual representation of how each input variable contributes to a model's predictions, explaining its importance on the model. It can be observed that ease of use is most significant predictor (39.93%), followed by platform experience (38.53%) of e-satisfaction among the retail investors using robo-advisory platforms. The projected results from machine learning technique are supporting the results obtained from structural equation modelling.

Figure 3: Relative Influence Plot
(Source: Authors' Own work)



The coefficient of determination obtained from SEM has a predictive ability of 44.6% towards e-satisfaction by the constructs, ease of use, aesthetics, platform experience and security. These platforms create an investing portfolio for the customer using complex algorithms (Yeh et al., 2023) taking into account several elements, including the client's risk tolerance, investing objectives, and market conditions

using principles of diversification to construct portfolios. The volatile movement of the securities from the market is captured and indulges in modifications of the client portfolio by portfolio rebalancing and restructuring to maintain the right proportion of asset allocation. It also reduces portfolio drift by advising to sell off the overweighed and buy under weighed securities using risk assessment tools ensuring optimal portfolio with effective diversification. They encourage cost reduction with minimal or no human interaction with integrated technology and this serves as a boon to the financially illiterate investors and creates financial knowledge with simple solutions round-the-clock. It comes with in-built data analysis for the various investment decisions, spending patterns, key performance indicators prompting the trend of the price movement, volatility in risk-return, and includes goal-based planning tools to assist investors in comprehending and achieving particular financial goals (Bai, 2021).

Retail investors who wish to minimize their expenses may find this to be appealing. They are advantageous for investors who like to manage their money digitally because they are available online. Usually, users have constant access to their portfolios and can make changes whenever they want (Saad et al., 2020). They frequently build diversified portfolios using current portfolio theory according to the investor's financial objectives and risk tolerance. Automate the process of investing, encompassing the rebalancing of the portfolio. Time can be saved, and the portfolio will remain consistent with the investor's objectives and risk tolerance (Brenner & Meyll, 2020). Customer satisfaction is influenced by fee structures that are transparent and reporting that is simple to read (Faradynawati & Söderberg, 2022). Investors value being aware of the costs associated with their investments and their performance. Investors frequently assess a robo-

advisor's portfolios based on their past performance with increased client satisfaction leading as result of positive returns asserting similar findings (Gan et al., 2021; Rossi & Utkus, 2020).

The current study was confined to only one autonomous platform. The aspiring researchers can dive more deeper into the other relevant avenues in this domain in terms of comparative study between the various platforms of comparative study between robo-advisory platforms and stockbrokers. There is scope for applying various technological models like TAM, UTAUT, TPB, etc that could be tested in different types of service robots like Agri-bots, and Audit-bots. There is scope to explore the application of the theoretical model using advanced technologies like Natural Language Processing (NLP), and many more to test the application of the model from the system development context.

Conclusion

Robo Advisory platforms are often used by investors because they provide customized services at a reasonable price and are accessible on a variety of electronic devices. The younger generation in urban regions is especially affected by this rise in popularity since they have more discretionary income. The customized service, cost efficiency, and accessibility on multiple electronic devices have led to an increase in the popularity of its usage among the younger population of various metropolitan cities empowered with greater disposable income. Thus, the robot advisory platform's ability to seamlessly integrate state-of-the-art technology with the changing needs of investors reinforces its role as a game-changer in the realm of modern investment management. Investors with different degrees of financial understanding can utilize them because of their user-friendly interfaces. They frequently offer educational tools and speak in plain English. Investors can use them to set specific financial objectives, like supporting school, purchasing a home, or saving for retirement.

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