International Journal of Business and Management Sciences
2026; 2(4): 157-160 | ISSN(O): 2693-3500
www.sciro.org/ijbms
DOI: 10.5281/zenodo.21974605

Role of Robo-Advisory Adoption Among Retail Investors

Dr E Nagaraju[1,*], **Kirana K J**[2], **Anushree H**[3].

[1] Assistant Professor, School of Management, CMR University, Bengaluru.
[2,3.] PG Scholar, Master Business Administration, School of Management, CMR University,Bengaluru.

Email address*: rajen1910@gmail.com
Received: 18.06.2026 | **Revised:** 22.07.2026 | **Accepted:** 07.08.2026

Abstract: Robo-advisors promise scalable and low-cost wealth management, yet their adoption in emerging markets depends on more than usefulness and interface simplicity. This study examines how cognitive, motivational and facilitating conditions shape attitude, behavioural intention and actual use among experienced retail investors in Chennai, India.

A cross-sectional survey was administered across five Chennai zones. From 400 questionnaires, 300 usable responses were retained. Respondents had at least one year of retail-investment experience. The integrated model draws on the Technology Acceptance Model, Theory of Planned Behaviour and motivational theory. Reliability, exploratory factor analysis, convergent validity, correlations and covariance-based structural equation modelling were used.

Self-efficacy was the strongest positive antecedent of attitude ($\beta = .31$), followed by usefulness ($\beta = .28$), facilitating conditions ($\beta = .25$), ease of use ($\beta = .22$), and compatibility ($\beta = .20$). Intrinsic motivation had a significant negative effect ($\beta = -.29$), contradicting the original positive-direction hypothesis. Attitude predicted behavioural intention ($\beta = .53$), which strongly predicted actual use ($\beta = .76$). Fit was acceptable but not unequivocal: CFI = .979, TLI = .942, GFI = .958, and RMSEA = .088.

The results reveal a competence-over-enjoyment mechanism. Experienced investors appear to treat Robo-advice as consequential financial infrastructure rather than a pleasurable technology. The paper reframes adoption strategy around investor agency, explainability, human escalation and reliable implementation support.

Keywords: Robo-advisory, wealth management, self-efficacy, intrinsic motivation, behavioural intention, technology adoption, India.

1. Introduction

Robo-advisors automate risk profiling, portfolio construction, rebalancing and digital communication. They can lower entry costs and extend investment guidance beyond high-net-worth segments. At the same time, investment advice is a high-stakes service: the consequences of an unsuitable risk profile, opaque recommendation or poorly timed portfolio action may persist long after an apparently easy interaction.

India presents a distinctive adoption context. Mobile access and app-based investing have expanded quickly, but investor knowledge, formal advice experience and confidence in automated recommendations remain uneven. Regulatory expectations concerning suitability, disclosure and accountability also mean that a Robo-advisor cannot be assessed like an ordinary consumer application.

Technology-acceptance studies generally expect usefulness, ease of use and intrinsic motivation to improve attitude. This paper tests a richer model that includes compatibility, facilitating conditions and self-efficacy, followed by attitude, intention and actual use. Its empirical contribution is an unexpected motivational asymmetry: competence strengthens attitude, but enjoyment-oriented motivation weakens it. We interpret this as evidence that investors value control and task effectiveness over hedonic engagement when algorithmic systems influence wealth.

2. Theory and hypotheses

2.1. Instrumental value

Perceived usefulness captures whether Robo-advice improves investment decision-making, while ease of use reflects effort required to interact with the platform (Davis, 1989). Both should strengthen attitude. Compatibility concerns alignment with existing investment routines, values and experience. Facilitating conditions represent access to knowledge, devices, support and organisational infrastructure.

2.2. Investor agency and self-efficacy

Self-efficacy is confidence in one's ability to perform required actions. In automated advice, it includes interpreting risk questions, understanding portfolio outputs and recovering from errors. Higher self-efficacy should reduce dependence anxiety and strengthen perceived control.

2.3. Intrinsic motivation in a high-stakes service

Intrinsic motivation normally supports voluntary technology use because the activity is interesting or enjoyable. Wealth management may reverse this relationship. Experienced investors may regard playful or stimulating interaction as inconsistent with seriousness, fiduciary care and downside risk. The direction is therefore theoretically contestable rather than automatically positive.

2.4. From attitude to actual use

The Theory of Planned Behaviour locates intention between evaluation and action. Positive attitude should strengthen intention, while intention should predict actual use. In digital investment settings, the intention-use link also depends on account access, investible funds and platform availability.

2.5. Hypotheses

- H1: Perceived usefulness positively influences attitude towards Robo-advisory.
- H2: Perceived ease of use positively influences attitude.
- H3: Intrinsic motivation influences attitude; the original study predicts a positive direction.
- H4: Compatibility positively influences attitude.
- H5: Facilitating conditions positively influence attitude.
- H6: Self-efficacy positively influences attitude.
- H7: Attitude positively influences behavioural intention.
- H8: Behavioural intention positively influences actual use.

3. Method

3.1. Design, participants and sampling

The descriptive cross-sectional study covered Chennai's East, West, North, South and Central zones. Snowball and purposive sampling were used. Eligible participants had at least one year of experience with retail investments, including stocks, bonds, mutual funds, exchange-traded funds, commodities, precious metals, real estate or derivatives. Four hundred questionnaires were distributed and 300 usable cases remained, a reported response rate of 75

3.2. Measures

The questionnaire integrated TAM, TPB and motivational constructs. It included 52 Likert-type items: usefulness (3), ease of use (6), attitude (6), intrinsic motivation (7), compatibility (3), facilitating conditions (8), self-efficacy (9), behavioural intention (6) and actual use (4). Expert review, content-validity assessment and a 50-investor pilot preceded the main study.

3.3. Sample characteristics

Table 1: Respondent profile. Source: Primary data

Characteristic	Distribution (N = 300)
Gender	Men 242 (80.67%); women 58 (19.33%)
Age	26-35 years: 50.67%; 36-45 years: 28.00%; other groups: 21.33%
Monthly income	> Rs. 1 lakh: 39.33%; Rs. 30,001-60,000: 24.67%; other: 36.00%
Education	Postgraduate: 60.67%; undergraduate: 29.33%; other: 10.00%
Investment knowledge	Moderate: 58.00%; extensive: 31.33%; limited: 10.67%

3.4. Analytical strategy

SPSS 21 and AMOS 21 were used. Internal consistency was assessed with Cronbach's alpha. PCA with Varimax rotation evaluated item structure; convergent validity used AVE and composite reliability. Pearson correlations described bivariate relationships. Covariance-based SEM tested the eight structural paths. Because the data are cross-sectional and non-probabilistic, coefficients are interpreted as associations rather than causal effects.

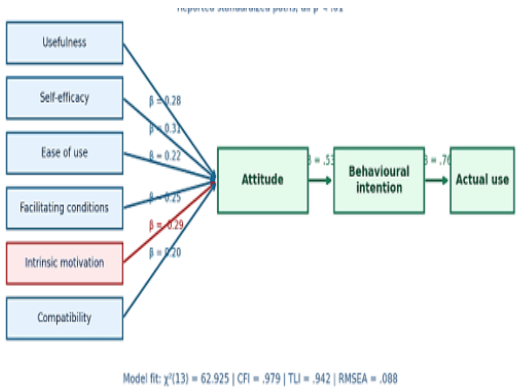

Figure 1: Competence-led Robo-advisory adoption model.

4. Results

4.1. Measurement quality

All reported alpha and CR values exceeded .90, and AVE ranged from .61 to .84. Although this supports internal consistency and convergence, very high alpha values may also indicate redundant item wording. Discriminant validity was not reported; the high correlation between intrinsic motivation and compatibility (r = .86) warrants further examination.

4.2. Model fit

Incremental fit indices were strong, but RMSEA = .088 and CMIN/df = 4.84 indicate residual approximation error. The model is therefore acceptable for exploratory theory testing, not a perfect fit. Reporting it as 'excellent' would overstate the evidence.

Table 2: Reliability and convergent validity. KMO = .761; Bartlett's $\chi^2(861) = 23,541.7$, $p < .001$.

Construct	Items	α	AVE	CR
Usefulness	3	.930	.82	.93
Ease of use	6	.954	.78	.95
Attitude	6	.964	.70	.96
Intrinsic motivation	7	.970	.80	.97
Compatibility	3	.919	.84	.92
Facilitating conditions	8	.947	.70	.95
Self-efficacy	9	.966	.61	.96
Behavioural intention	6	.926	.68	.93
Actual use	4	.922	.77	.93

Table 3: Reported standardised structural estimates.

Path	β	SE	CR	p	Decision
Usefulness → attitude	.28	.04	6.17	$< .001$	Supported
Self-efficacy → attitude	.31	.05	6.29	$< .001$	Supported
Ease of use → attitude	.22	.04	4.65	$< .001$	Supported
Facilitating conditions → attitude	.25	.04	5.58	$< .001$	Supported
Intrinsic motivation → attitude	-.29	.04	-5.00	$< .001$	Opposite direction
Compatibility → attitude	.20	.05	3.27	$< .01$	Supported
Attitude → intention	.53	.05	10.74	$< .001$	Supported
Intention → actual use	.76	.04	20.26	$< .001$	Supported

Table 4: Model-fit assessment

Index	Reported value	Reference	Assessment
χ^2 / df	62.925 / 13	CMIN/df = 4.84	Tolerable, relatively high
GFI / AGFI	.958 / .901	$> .90$	Acceptable
NFI / TLI / CFI	.974 / .942 / .979	$> .90$	Acceptable
RMR / RMSEA	.048 / .088	Lower preferred	RMR good; RMSEA borderline

Incremental fit indices were strong, but RMSEA = .088 and CMIN/df = 4.84 indicate residual approximation error. The model is therefore acceptable for exploratory theory testing, not a perfect fit. Reporting it as 'excellent' would overstate the evidence.

5. Discussion

5.1. The competence-over-enjoyment mechanism

Self-efficacy was the largest positive antecedent of attitude. Experienced investors appear more receptive when they feel capable of understanding and controlling the digital journey. This makes agency central to Robo-advisory adoption: a platform should not merely be effortless; it should make the investor feel competent.

5.2. The intrinsic-motivation paradox

Intrinsic motivation was significantly negative, contrary to the source hypothesis and narrative. One explanation is domain seriousness: enjoyment-oriented interfaces may create discomfort when losses, retirement or family wealth are involved. A second is statistical suppression caused by the high overlap between intrinsic motivation and compatibility. A third is item wording or reverse-coding error. The finding is important but must be replicated before it is treated as a stable behavioural mechanism.

5.3. Intention is the conversion mechanism

Attitude predicted intention moderately, whereas intention predicted actual use strongly. Providers should therefore distinguish favourable perceptions from implementation readiness. Onboarding completion, account funding, suitability assessment and trust in execution may determine whether positive evaluation becomes investment behaviour.

5.4. Emerging-market implications

The sample was investment-experienced, male-dominated and highly educated. These characteristics may increase confidence and reduce general adoption barriers. Inclusive expansion requires testing with novice, female, older and lower-income investors, for whom explanation, assisted advice and grievance handling may be more decisive.

6. Practical and policy implications

Build investor competence through risk simulations, plain-language portfolio explanations and transparent rebalancing logic.

Provide human escalation for life events, unusual financial circumstances and disputed risk profiles.

Treat intrinsic-motivation features cautiously; avoid gamification that trivialises risk or encourages excessive trading.

Measure whether users understand recommendations, not only whether they complete onboarding.

Audit suitability, conflicts of interest, fees, model changes and subgroup outcomes throughout the product lifecycle.

For Indian regulators and wealth-management providers, Robo-advice should be positioned as regulated advice delivered through technology, not merely software. Governance must preserve suitability, explainability, consent, data protection and access to accountable human review.

7. Limitations and future research

The non-probability sample, single-city setting and 75% usable-response rate limit generalisation. Common-method and non-response bias were not assessed. Discriminant validity, multicollinearity diagnostics, indirect effects, explained variance and confidence intervals were not reported. The negative intrinsic-motivation path may reflect suppression, wording or coding. The actual-use measure is self-reported, and cross-sectional data cannot establish temporal causality.

Future studies should preregister the model, verify item direction, report HTMT and VIF, test indirect effects with bootstrapping and collect objective usage records. Multi-group invariance should be examined by gender, age, wealth and advisory experience. Experiments can compare purely automated, human-assisted and human-led advice under market volatility.

8. Conclusion

Robo-advisory adoption among Chennai investors is best understood as a competence-led process. Usefulness, ease, compatibility, facilitating conditions and especially self-efficacy strengthen attitude. Attitude shapes intention, and intention strongly converts into use. Enjoyment, however, is not automatically beneficial in a consequential financial service.

The strategic lesson is that credible Robo-advice should make investors feel informed, capable and protected. Platforms that optimise only frictionless interaction may miss the deeper requirement: technology must support investor agency while preserving access to explanation, correction and human judgment.

References

1. Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T
2. Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.
3. Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial intelligence in FinTech: Understanding robo-advisors adoption among customers. Industrial Management & Data Systems, 119(7), 1411–1430. https://doi.org/10.1108/IMDS-08-2018-0368
4. Bhatia, A., Chandani, A., Atiq, R., Mehta, M., & Divekar, R. (2021). Artificial intelligence in financial services: A qualitative research to discover robo-advisory services. Qualitative Research in Financial Markets, 13(5), 632–654.
5. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
6. Fisch, J. E., Labouré, M., & Turner, J. A. (2019). The emergence of the robo-advisor. In J. Agnew & O. S. Mitchell (Eds.), The disruptive impact of FinTech on retirement systems. Oxford University Press.
7. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104
8. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage.
9. Jung, D., Dorner, V., Glaser, F., & Morana, S. (2018). Robo-advisory: Digitalization and automation of financial advisory. Business & Information Systems Engineering, 60, 81–86. https://doi.org/10.1007/s12599-018-0521-9
10. Jung, D., Glaser, F., & Köpplin, W. (2019). Robo-advisory: Opportunities and risks for the future of financial advisory. In V. Nissen (Ed.), Advances in consulting research. Springer.
11. Kaya, O., & Schildbach, J. (2017). Robo-advice: A true innovation in asset management. Deutsche Bank Research.
12. Lourenço, C. J. S., Dellaert, B. G. C., & Donkers, B. (2020). Whose algorithm says so: The relationships between type of firm, perceptions of trust and expertise, and the acceptance of financial robo-advice. Journal of Interactive Marketing, 49, 107–124.
13. Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure perceptions of adopting an information technology innovation. Information Systems Research, 2(3), 192–222. https://doi.org/10.1287/isre.2.3.192
14. Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill
15. Sironi, P. (2016). FinTech innovation: From robo-advisors to goal based investing and gamification. Wiley
16. Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. MIS Quarterly, 15(1), 125–143. https://doi.org/10.2307/249443
17. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540