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Investing in the future: an integrated model for analysing user attitudes towards Robo-advisory services with AI integration

Sandeep Singh
Department of Commerce, Shaheed Bhagat Singh College, University of Delhi, New Delhi, India, and

Atul Kumar
Department of Commerce, P.G.D.A.V. College, University of Delhi, New Delhi, India

Abstract

Purpose – Recognizing the importance of Robo-advisors in digital financial services, this paper aims to analyze the users' perception and acceptability of artificial intelligence (AI) in digital investment solutions using an extended "Technology Acceptance Model" (TAM).

Design/methodology/approach – The model is tested using 454 online valid responses received from Indian Fintech users via direct path analysis, mediation and moderation.

Findings – The study's findings show that trust, perceived usefulness and perceived risk all significantly impact users' attitudes towards Robo-advisors. In contrast, ease of use and social influence did not impact users' attitudes statistically. Furthermore, the results indicate that their attitudes and ease of use influence users' intentions to adopt Robo-advisors. Moreover, the moderation effect of gender partly supports the overall model. Specifically, in the path between attitudes and their antecedents, gender plays a role in influencing the relationships among these variables. This aligns with preliminary research in the field, providing additional insight into how gender may moderate the factors influencing users' attitudes and intentions regarding Robo-advisory services.

Research limitations/implications – This research study also reveals that trust, perceived risk, ease of use and demographic factors influence the adoption of Robo-advisory services. It is functional, but its sample selection is not probabilistic and overly emphasizes gender. Future research should use probabilistic sampling, other demographic factors and experience and situational factors. Also, it is necessary to examine how convenient and satisfying it is to communicate with service providers. Filling these gaps will improve the knowledge of consumer behaviour in the context of Fintech adoption and develop the current research.

Practical implications – This study posits that perceived usefulness, trust, perceived risk and ease of use remain core determinants of adopting Robo-advisory services. So, to improve the level of trust of users, it is necessary to develop security measures, data clarity and quality and customer support. Enhancing ease of use by incorporating better interface gestures is always beneficial for increasing the number of users and their level of satisfaction. As identified in previous studies, practical solutions will be achieved by pursuing the increased

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use of technology while leveraging AI for personal services and minimizing perceived risks, which will strengthen more advanced security measures as well as sufficiently clear communication.

Originality/value – The paper aims to extend the TAM by incorporating measures of trust and social influence to identify the factors that drive the adoption of Robo-advisors. In doing so, the paper may contribute to developing a more comprehensive understanding of the factors that shape consumers' attitudes and intentions towards these technologies. Moreover, the paper appears to examine the moderating effect of gender on attitude and its predictors, which could provide insights into how gender characteristics may impact the adoption of Robo-advisors.

Keywords Robo advisory, TAM, Perceived usefulness, Perceived ease of use, Social influence, Trust, Perceived risk, Fintech

Paper type Research paper

1. Introduction

The focus of prior research in this field has been on the legality, the service structure, the supply side of Robo advisory and excluding the perspective of clients. Furthermore, the scant literature on artificial intelligence (AI) adoption in the Fintech sector has revealed that implementation is still in its nascent stage. Moreover, previous studies on Robo-advisory adoption conducted in Italy (Milani, 2019), Malaysia (Hu *et al.*, 2019) and India (Manrai and Gupta, 2022) have identified gaps regarding consumers' lack of basic knowledge about AI in Fintech. More importantly, investors do not trust it because they think it is riskier than traditional investing options (Belanche *et al.*, 2019).

In addition, the literature indicates that Fintech users often consider functional and technical factors, including perceived risk (Milana and Ashta, 2021; Mohammadi, 2015; Lee and Chen, 2022), when making decisions, which can affect their intention to adopt Robo-advisory services (RAS). The other most significant aspect of user adoption is trust (Manrai and Gupta, 2022; Sharma *et al.*, 2017; Chuang *et al.*, 2016; Bhatia *et al.*, 2020), which is imperative for automated investments. To fill this crucial research gap, we used the "Technology Acceptance Model" (TAM) to investigate why people use Robo-advisors. The TAM (Davis, 1989; Davis *et al.*, 1992; Venkatesh and Bala, 2008) measures consumers' intentions based on their attitudes towards usage by analysing perceived ease of use (PEOU) and perceived usefulness (PU). Therefore, the current research adopts an extended modified version of TAM to incorporate two important factors in the RAS acceptance model: trust and perceived risk.

This research is structured as follows: Section 2 reviews the relevant literature and introduces the conceptual framework, along with the formulation of hypotheses. Section 3 details the data collection process, while Section 4 provides an in-depth explanation of the research methodologies employed. Section 5 presents the research findings and discusses their implications. The 6th section discusses the practical implication of the research and the 7th section addresses the limitations of the study and outlines potential areas for future research..

2. Literature review

Research has suggested theories and models for adopting and using new technologies, such as the theory of planned behaviour (Ajzen, 2002); innovation diffusion theory (Venkatesh and Bala, 2008); the "Technology Acceptance Model" (TAM) (Davis, 1989b); and unified theory of acceptance and use of technology (Venkatesh *et al.*, 2003; Jaiswal *et al.*, 2022a). Among all theories, "Technology Acceptance Model" has been widely accepted because of its simplicity and clarity of application (King *et al.*, 2006). The primary intent of TAM was to rectify the flaws in the 1986 theory of reasoned action (TRA). TAM basically examines people's psychological behaviour when using technology.

The fundamental premises of TAM are the behavioural intentions related to adopting new technology are influenced majorly by two factors: the PEOU, which refers to the perception that the latest technology is effortless and the PU, which refers to the perception of how well a new technology is for improving performance efficiency and usability (Davis, 1989; Roy *et al.*, 2018). This view is consistent with that of many scholars who argue that PU and PEOU do not provide an accurate indicator of the individual's behaviour and intentions. As a result, other technology-innovative adoption studies have brought new variables to the original TAM, incorporating social influence (SI), perceived risk and perceived trust (Alalwan *et al.*, 2016a, 2016b; Hu *et al.*, 2019; Manrai and Gupta, 2022; Oliveira *et al.*, 2016). In addition, TAM comes up with the option to integrate foreign constructs as factors influencing the adoption (Davis, 1989; Jaiswal *et al.*, 2021). Considering all the previous studies' suggestions, we have added the crucial factors with classical TAM (SI, perceived risk and perceived trust) in the conceptual model (Figure 1).

2.1 Conceptual framework and hypothesis development

2.1.1 Perceived usefulness. According to Hartono (2008), PU refers to people's perception of how a system will improve their performance. Regarding RAS-driven Fintech services, the users get advantages such as secure and profitable advice and accurate portfolio management. The convenience that RAS offers particularly in personal banking and aspects such as round-the-clock customer service fortify this notion (Liu *et al.* (2023)). Innovations in technologies such as the adoption of electronic wallets to health care shift the adoption intentions by PU (Oliveira *et al.*, 2016; Hu *et al.*, 2019).

Robo-advisors are more efficient, cheaper and accessible than conventional services, and as people learn about these benefits, they develop a favourable attitude towards them. According to the responses of the participants in Agyei *et al.* (2020), PU has a positive correlation with the attitudes and the willingness to adopt RAS. The following hypothesis was developed from the viewpoint of the earlier studies:

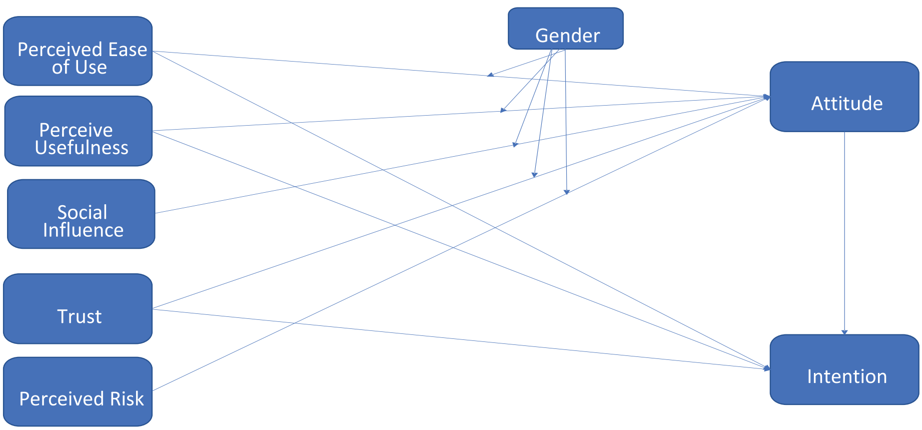

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Figure 1. Conceptual framework

H1. Perceived usefulness (PU) positively affects users' attitudes (ATT) towards using Robo-advisories services.

H2. Perceived usefulness (PU) positively affects users' intention to adopt Robo-advisories services.

2.1.2 Perceived ease of use. PEOU, a key TAM component, refers to users' belief that using a system requires minimal effort (Davis, 1989a). Research consistently shows PEOU positively influences attitudes and intentions towards new technologies, including e-learning, digital banking and e-commerce platforms (Hu *et al.*, 2019; Jaiswal *et al.*, 2022a; Suryono *et al.*, 2020). Users expect AI to be user-friendly, necessitating minimal learning effort.

In Fintech, Robo advisors enhance service quality, addressing gaps in traditional finance (Lee and Chen, 2022; Agyei *et al.*, 2020; Hu *et al.*, 2019). PEOU not only directly impacts adoption intent but also indirectly influences it through users' attitudes towards innovative technology adoption. We develop the following hypothesis based on the above statements:

H3. Perceived ease of use (PEOU) positively affects users' attitudes (ATT) towards Robo-advisories adoption.

H4. Perceived ease of use (PEOU) positively affects users' intention to adopt Robo-advisories services.

2.1.3 Social influence. Koenig-Lewis *et al.* (2015) emphasize the societal creation of psychological reality, asserting that individuals shape their identity based on socially defined terms. The theory of social comparison, introduced by Festinger, is used to elucidate SI, contending that individuals rely on others to mitigate the fear of making incorrect decisions and seek approval within their social groups to enhance acceptance (Warshaw, 1980).

In the realm of technology adoption, SI emerges as a pivotal variable impacting attitudes and adoption intentions (Singh and Kaur, 2017). Previous studies highlight positive associations between social norms and users' attitudes and intentions to adopt emerging technologies like ubiquitous computing and near-field communication (Chung *et al.*, 2017):

H5. Social influence (SI) positively affects users' attitudes (ATT) towards Robo-advisories adoption.

2.1.4 Perceived trust. Trust, as defined by Al Ajam (2013), involves a party's willingness to be vulnerable based on the expectation that the other party will perform a specific action crucial to trust. In adoption studies, trust has been a longstanding subject of investigation (Venkatesh and Bala, 2008). In technology adoption, concerns about trust often stem from a lack of security and privacy institutional frameworks (Biswas *et al.*, 2021; Olsen, 2012). Users may be hesitant to trust a system that lacks robust safeguards. Notably, building trust is facilitated when users find it easier to encourage desired behaviour, enhancing their inclination to use the service (Ryu, 2018). This connection between ease of use, user encouragement and trust in the service provider forms the basis for the proposed hypothesis:

H6. Perceived trust (TRU) positively affects users' attitudes (ATT) towards Robo-advisories adoption.

2.1.5 Perceived risk. Previous studies consistently demonstrate a negative correlation between perceived risk and the adoption of new financial technologies, spanning mobile payments (Zhang *et al.*, 2012; Jaiswal *et al.*, 2021), internet banking (Biswas *et al.*, 2022; Marakarkandy *et al.*, 2017) and e-services (Mogaji *et al.*, 2021). Privacy and security risks, particularly concerning personal information, emerge as predominant concerns among users adopting new financial technology (Bansal *et al.*, 2010). In the context of Fintech services, customers' concerns about the confidentiality and security of information displayed are higher compared to the context of well-established financial institutions (Bruckes *et al.*, 2019). This study focuses on risks perceived by users of Robo advisors relating to financial security and the privacy of their information that would be the basis of the following hypothesis:

H7. Perceived risk (PR) negatively affects users' attitudes (ATT) towards Robo-advisories adoption.

2.1.6 Attitudes. Another well-documented principle in the TRA and the TAM is that of attitude and intention. These models explain that perceived attitudes concerning technology or innovation play a leading role in the behavioural intention to adopt or use it (Tabatabaei Nasab *et al.*, 2014).

Attitude on the other hand is a disposition towards or view for or against an object or behaviour or a tendency to respond in a particular manner (Shanmugam *et al.*, 2014). In the case of Robo-advisors' services, attitude reflects consumers' perceptions concerning the services offered including PU, ease of use and other factors (Yeh, 2023).

In contrast, intention is one's mindset or preparedness to perform a particular behaviour. When it comes to Robo-advisors the Intention to Use Services (ITUS) will involve a consumer's willingness to engage and use such platforms for the management of their finances (Wu and Gao, 2021).

Studies have shown that perceived use or intent to adopt a technology or innovation is highly correlated with attitudes towards the technology or innovation (Wu and Gao, 2021).

In other words, subjects who have a positive attitude towards Robo-advisor are more likely to have a future behavioural intention to use Robo-advisor:

H8. Users' attitude (ATT) positively affects the intention to use Robo advisory services.

2.1.7 Moderating role of gender. Gender is a crucial moderating element in the acceptance and usage of emerging technology, e.g. (Agyei *et al.*, 2020; Bhatia *et al.*, 2020; Chawla and Joshi, 2018; Faqih, 2016; Jaiswal *et al.*, 2022b). This could be because men and women have distinct decision-making processes and value different things differently when evaluating behaviours (Venkatesh *et al.*, 2003). Consumer behaviour literature suggests that males and females may display technological optimism, but men may be more likely to adopt new technology to increase profits (Hoffman, 1972). Following are the hypotheses derived from the above statements:

H9a. Gender moderates the association between the TRU and ATT.

H9b. Gender moderates the association between the PEOU and ATT.

H9c. Gender moderates the association between the PU and ATT.

H9d. Gender moderates the association between the SI and ATT.

H9e. Gender moderates the association between the PR and ATT.

3. Methodology

3.1 Field survey and sample

The research hypotheses were tested through a two-phase questionnaire. Initially, students with demat accounts and active involvement in investing were surveyed across various North Indian colleges. Subsequently, the questionnaire was distributed to active investors of different age groups, including friends, colleagues and groups associated with brokerage firms, via email. The focus on young users, specifically millennials, was driven by their higher digital awareness and familiarity with AI (Chawla and Joshi, 2018). Data collection occurred between August 2022 and October 2022, yielding 481 responses. After excluding erroneous replies, a sample size of 454 was used for analysis.

Structured questionnaires covered demographic information such as gender, age, occupation, income level and investment level. To ensure content validity, the questionnaire was written in English and reviewed by language experts. A pre-test involving 50 respondents, including students and academicians, validated the scales. The final data collection, ensuring no data from the pilot test influenced results, used a cross-sectional, quantitative research approach. Structural equation modelling (SEM) via IBM-AMOS software was used for data analysis.

According to a descriptive analysis of the respondents (shown in Table 1), 72.6% were male respondents while 27.4% were female. A total of 73.3% of participants were aged between 18 and 25, 14.5% were ranged from 26 to 35 years old, 21% were ranged from 20 to 30 and 12% were above 35. Since the data was collected mostly from undergraduate students, 50% of the sample were from undergraduate students, 17.5% were pursuing post-graduate, 21.4% were

Table 1. Descriptive analysis of a sample

S.no.	Category	Frequency	%
Gender			
1	Male	340	72.6
2	Female	128	27.4
Age group			
1	18–25 years	343	73.3
2	26–35 years	68	14.5
3	36–45 years	25	5.3
4	46–60 years	30	6.4
5	Above 60	2	0.4
Education level			
1	10 + 2	100	21.4
2	Other professional courses	31	6.6
3	PhD	21	4.5
4	Post graduate	82	17.5
5	Undergraduate	234	50
Occupation			
1	Housewife	10	2.1
2	Private sector employee	76	16.2
3	Public sector employee	60	12.8
4	Self-employed/business	26	5.6
5	Student	293	62.6
6	Unemployed	3	0.6
Annual income			
1	0–3 lakh	306	65.4
2	3–5 lakh	37	7.9
3	5–10 lakh	59	12.6
4	above 10 lakh	66	14.1

Source: Table created by authors

pursuing 12th, 6.6% were from other professional courses and only 4.5% were pursuing PhD. When it comes to the occupation of the respondents 60% were students, 16.2 were corporate employees, 12.8% were related to the public sector, 5.6 were self-employed, 2.1% of the total respondents were housewives and only 0.6 were unemployed.

3.2 Research measures

An online survey using Google Forms was distributed via WhatsApp and email, using a five-point Likert scale. The questionnaire comprised two sections: Section 1 covered demographic details like gender, age, educational qualification and annual income. Section 2 focused on respondents' attitudes towards Robo-advisory, incorporating measures of PU, PEOU, attitude (AT), intention of adoption (IA) and SI from (Yeh *et al.*, 2023). Additionally, trust (TRU) and perceived risk, adapted from (Manrai and Gupta, 2022), were included, all appropriately tailored for the Indian context.

4. Analysis and results

Prior to conducting confirmatory factor analysis (CFA), a comprehensive examination of the data was undertaken to address potential issues like missing values, multicollinearity and outliers. This meticulous pre-analysis step aimed to enhance the reliability and integrity of the subsequent CFA.

The root mean square error of approximation (RMSEA) was 0.08, aligning with the recommendations of Bentler (1992) and Bentler and Bonett (1980), further validating the adequacy of the measurement model.

Specific fit statistics for the CFA measurement model provided additional depth to the assessment. The chi-square statistic ($\chi 2$) of 468.455 with 278 degrees of freedom yielded a $\chi 2$/df ratio of 1.750 and a highly significant p-value (< 0.000), indicating that the model adequately represented the observed data. Furthermore, the CFI, NFI and TLI values (0.975, 0.945 and 0.971, respectively) exceeded the 0.90 benchmark, emphasizing the high level of fit. The GFI, at 0.926, contributed to the overall assessment of model goodness of fit.

The RMSEA, within the suggested range at 0.04, added confidence to the appropriateness of the measurement model. The standardized root mean residual (SRMR) of 0.322 also indicated a reasonable level of model fit.

Table 2 presents the confirmatory factor analysis results for the measurement model (CFA), displaying means, standard deviations and factor loadings for each construct and its items. Notably, all factor loadings exceeded the recommended threshold of 0.7, affirming the robustness of the measurement model.

4.1 Reliability and validity

Turning to the assessment of reliability and validity, the study used CFA following the established criteria of Fornell and Larcker (1981). Convergent validity was established through statistically significant CFA factor loadings ($p < 0.05$), as meticulously outlined in Table 2. Each construct surpassed the average variance extracted (AVE) threshold of 0.50, affirming the study's convergent validity. Additionally, the reliability of each construct, exceeding the 0.70 benchmark, underscored the research instruments' reliability (see Table 3).

Discriminant validity, a critical aspect of construct validation, was rigorously confirmed by comparing construct correlations with the square root of the AVE for each construct, as per Fornell and Larcker (1981). The meticulous findings in Table 3 illustrate that the square root of the AVE for each construct surpassed its correlations with other factors, thereby conclusively establishing discriminant validity.

Table 2. Confirmatory factor analysis results for the measurement model (CFA)

Construct and items	Mean	Std. deviation	SL
Perceived usefulness (PU)			
PU1	3.78	1.035	0.810
PU2	3.83	0.981	0.755
PU3	3.83	0.982	0.732
PU4	3.84	0.967	0.735
Perceived ease of use (PEOU)			
PEOU1	3.71	1.026	0.745
PEOU2	3.80	0.983	0.738
PEOU3	3.79	0.974	0.764
PEOU4	3.77	0.966	0.793
Social influence (SI)			
SI1	3.30	1.180	0.716
SI2	3.61	1.052	0.712
SI3	3.42	1.130	0.794
SI4	3.53	1.154	0.768
Trust (TRU)			
TRU1	3.68	1.028	0.825
TRU2	3.65	1.036	0.833
TRU3	3.67	1.032	0.848
TRU4	3.56	1.094	0.753
Perceived risk (PR)			
PR1	3.295	1.2435	0.852
PR2	3.17	1.223	0.879
PR3	3.23	1.213	0.885
PR4	3.20	1.166	0.817
Attitude (ATT)			
ATT1	3.79	0.963	0.852
ATT2	3.79	1.021	0.856
ATT3	3.80	1.027	0.823
Intention of adoption (INT)			
INT1	3.56	1.114	0.849
INT2	3.53	1.162	0.912
INT3	3.20	1.286	0.811

Notes: SL = standard loadings; M = mean; SD = standard deviation; SMC = squared multiple correlation; PU = perceived usefulness; PEOU = perceived ease of use; SI = social influence; TRU = trust; PR = perceived risk; ATT = attitude; INT = intention to adoption
Source: Table created by authors

Furthermore, the study's items demonstrated robust scores, all exceeding the mid-scale point of 2.5, as showcased in Table 2. A nuanced analysis of respondent perceptions revealed that, on average, PU received the highest rating (M = 3.8), followed closely by attitude (ATT, M = 3.79), perceived ease of use (PEOU, M = 3.77), trust (TRU, M = 3.64), SI (SI, M = 3.46), intention to adoption (INT, M = 3.43), perceived risk (PR, M = 3.28) and perceived ease (PE, M = 3.225). These findings collectively contribute to a compelling narrative of the study's reliability, validity and overall impact.

Initially, all CFA factor loadings exhibited statistical significance at the $p < 0.05$ level, as detailed in Table 2. This signifies the strength of the relationship between each observed

Table 3. CFA discriminant validity and reliability values

Contruct name	Alfa	CR	AVE	PR	PU	PEOU	TRU	SI	INT	ATT
PR	0.918	0.918	0.737	0.859						
PU	0.843	0.844	0.576	0.161**	0.759					
PEOU	0.845	0.846	0.578	0.240***	0.655***	0.761				
TRU	0.888	0.888	0.666	0.154**	0.744***	0.669***	0.816			
SI	0.834	0.835	0.56	0.172**	0.649***	0.628***	0.714***	0.748		
INT	0.889	0.893	0.737	0.159**	0.481***	0.461***	0.535***	0.493***	0.858	
ATT	0.88	0.881	0.712	0.07	0.636***	0.508***	0.630***	0.513***	0.483***	0.84

Notes: This note outlines key metrics and factors vital for assessing the reliability and validity of the measurement model. The abbreviations provided, such as average variance extracted (AVE), Cronbach's alpha (α) and construct reliability (CR), serve as essential indicators in this evaluation. The note specifies the constructs under consideration, including perceived Usefulness (PU), perceived ease of use (PEOU), social influence (SI), trust (TRU), perceived risk (PR), ATT (attitude) and INT (intention to adoption); ***$p <$ 0.001, **$p < 0.010$, *$p < 0.050$ and † $p < 0.100$
Source: Table created by authors

variable and its underlying latent construct. Following this, the AVE for each of the study constructs surpassed the recommended threshold of 0.50 as shown in Table 3. This indicates that a substantial proportion of the variance in the observed variables was effectively captured by their respective latent constructs.

Overall impact: $\chi 2 = 9.489$, df = 6, $\chi 2$/df =1.581, $p < 0.000$, CFI = 0.998, NFI = 0.995; TLI = 0.988, GFI = 0.994, RMSEA = 0.036, SRMR = 0.0159.

4.2 Hypotheses testing: direct effects

The following section explores the hypotheses results for the present study. The summary of the hypotheses results has been provided in Table 4.

In the examination of direct effects, the study delves into the relationships between various factors. Notably, trust was found to significantly impact attitude ($\beta = 0.337$, $p < 0.05$), leading to the acceptance of *H1*. This suggests that higher levels of trust in Robo-advisory

Table 4. Test of hypothesis

Hypothesis no.	Hypothesis	Beta	*t*-value (critical ratios)	Result
H1	TRU → ATT	0.337***	5.185	Supported
H2	SI → ATT	−0.009	−0.154	Not supported
H3	PEOU → ATT	0.031	0.586	Not supported
H4	PU → ATT	0.0.426***	7.155	Supported
H5	PR → ATT	−0.061 †	−1.836	Supported
H6	ATT → INT	0.282***	5.27	Supported
H7	PEOU → INT	0.231***	4.128	Supported
H8	PU → INT	0.166	2.552	Not supported

Notes: PU = perceived usefulness; PEOU = perceived ease of use; SI = social influence; TRU = trust; PR = perceived risk; ATT = attitude; INT= intention to adoption; ***$p < 0.001$, **$p < 0.010$, *$p < 0.050$ and †$p <$ 0.100
Source: Table created by authors

result in a more favourable attitude towards it. Conversely, *H2*, exploring the influence of SI on attitudes, did not receive support ($\beta = -0.009$, $p > 0.05$). Similarly, the link between PEOU and Attitude ($\beta = 0.031$, $p > 0.05$) was not substantiated, challenging the support for *H3*. However, PU was found to significantly influence Attitude ($\beta = 0.426$, $p < 0.05$), supporting *H4*. Additionally, the study revealed a significant negative impact of Perceived Risk on Attitude ($\beta = -0.061$, $p < 0.05$), endorsing *H5*. This implies that higher perceived risks associated with Robo-advisory lead to less favourable attitudes.

Moving on to intentions, the relationship between Attention and Intention was supported ($\beta = 0.282$, $p < 0.05$), confirming *H6*. Similarly, *H7*, examining the link between PEOU and Intention, found support ($\beta = 0.231$, $p < 0.05$). However, the relationship between PU and Intention ($\beta = 0.166$, $p > 0.05$) was not significant, leading to the rejection of *H8*. In summary, five out of the eight direct hypotheses were accepted, indicating varied impacts on attitudes and intentions.

4.3 *Mediation effects*

Following section explores the hypotheses results for mediation effects. The summary of the hypotheses results has been provided in Table 5.

The study further explores mediation effects using the bootstrapping method, generating 2,000 bootstrap samples with 95% confidence intervals. The mediation analysis focused on the role of Attitude in mediating the relationship between PU and Intention. Results revealed a significant positive indirect impact ($\beta = 0.120$, $p = 0.001$), supporting *H9a*. Additionally, in the presence of the mediator (Attitude), the direct effect of PU on Intention remained significant ($\beta = 0.166$, $p = 0.0$). Therefore, Attitude was confirmed as a mediator in the relationship between PU and Intention. However, *H9b* was rejected as the mediating role of Attitude between PEOU and Intention was not significant, indicating nonsupport for this mediation path.

4.4 *Results of multi-group analysis: moderation of gender*

The study conducted a multi-group analysis to examine the moderating effect of gender on the linkage paths between attitude and its predictors (PU, PEOU, SI, TRU and PR), as outlined in Table 6.

4.5 *Results of multi-group analysis: moderation of gender*

The study conducted a comprehensive multi-group analysis to investigate the moderating influence of gender on the paths between attitude and its predictors (PU, PEOU, SI, TRU and PR), as detailed in Table 6. This method allowed for the examination of gender-based differences.

Table 5. Mediation analysis summary

Hypothesis no.	Relationship	Standardized direct effect	Standardized indirect effect	Confidence interval	*p*-value	Conclusion
H9a	PU → ATT → INT	0.166 (0.028)	0.12	0.077 to 0.176	0.001	Partial mediation
H9b	PEOU → ATT → INT	0.231 (0.001)	0.009	−0.15 to 0.039	0.530	No mediation

Source: Table created by authors

Table 6. Multi-group analysis – moderation of gender

Effect		Gender	Beta	S.E.	*p*-value	*t*-value	Difference	Moderation
H10a	PU → ATT	Male	0.742	0.036	0.000	–	1.420 ns
		Female	0.578	0.078	0.000	–	
H10b	PEOU → ATT	Male	0.522	0.035	0.000	2.361*	Yes
		Female	0.338	0.059	0.000	–	
H10c	SI → ATT	Male	0.635	0.042	0.000	2.463*	Yes
		Female	0.407	0.084	0.000	–	
H10d	TRU → ATT	Male	0.723	0.035	0.000	–	0.662 ns
		Female	0.586	0.077	0.000	–	
H10e	PR → ATT	Male	0.127	0.040	0.021	2.363*	Yes
		Female	−0.130	0.076	0.152	–	

Notes: $^*p < 0.01$; ns = not significant
Source: Table created by authors

Key findings:

(1) Moderation of gender supported (Yes/Yes):

- *PEOU –-> ATT (*t *= 2.361):** The moderation effect of gender on the path between PEOU and Attitude (ATT) is highly significant, supporting gender-based differences.
- *SI –-> ATT (*t *= 2.463):** Gender significantly moderates the path between SI and Attitude (ATT), indicating distinct gender-related impacts.
- *PR –-> ATT (*t *= 2.363):** The moderation effect of gender on the Perceived Risk (PR) to Attitude (ATT) path is highly significant, emphasizing gender-based variations.

(2) Moderation of gender not supported (No/No):

- PU –-> ATT (*H10a*): The moderation effect of gender on the PU to Attitude (ATT) path was not supported, suggesting no significant gender-related differences.
- TRU –-> ATT (*H10d*): Gender did not significantly moderate the Trust (TRU) to Attitude (ATT) path, indicating no gender-related distinctions.

In conclusion, the multi-group analysis provides valuable insights into the nuanced influence of gender on the relationships between key factors and attitudes towards Robo-advisory.

5. Discussion and implications

The study investigates attributes influencing behavioural decisions regarding the adoption of RASs in the Indian context. It uses a revised version of the TAM by incorporating additional variables: SI, trust and perceived risk. Attitudes are examined as a mediating factor between predictors and adoption intentions, with the moderation of gender also considered. The model is analysed using SEM, confirming its robustness.

Results indicate that attitudes towards Robo-advisors are significantly influenced by PU and ease of use. Trust also plays a significant role, indicating consumer confidence in technology. However, the relationship between social norms and attitudes is not significant, suggesting consumers do not rely on peer recommendations.

Perceived risk negatively impacts attitudes towards Robo-advisory adoption, highlighting concerns about data privacy and security. Despite this, a positive relationship is observed between favourable attitudes and intention to use Robo-advisors, indicating potential for market engagement.

Multi-group analysis reveals gender differences in attitude moderation, with males showing a stronger impact of PEOU, SI and perceived risk on attitudes compared to females. However, gender differences do not significantly influence the relationship between PU, trust and attitudes.

5.1 Research findings and implications

This research work is consistent with other studies on TAM and Fintech services, including the Robo-advisor. Previous studies have cited PU and PEOU as the antecedents of users' attitudes towards technological innovations. For instance, the seminal study by Davis (1989) revealed that PU and PEOU are two fundamental constructs of the TAM.

Moreover, Oliveira *et al.* (2016) and Hu *et al.* (2019) have also supported that PU plays a subjective significant role in shaping the attitudes and adoption intentions towards Fintech services. Along the same line, the findings of the current study regarding the positive association between trust and user attitudes towards Robo-advisors are supported by prior studies that underline trust plays the part in technology acceptance and specifically in the financial sector where data, security and privacy are concerns.

Prior studies have found that pressure from peers affects the use of technology in daily life significantly. For instance, Koenig-Lewis *et al.*, 2015 pointed to the fact that the influence of other users is essential in determining Business Process Automation (BPA) adoption. Further, Chung *et al.* (2017) as well as Singh and Kaur (2017) have pointed out the positive link between social norms and user perception and behavioural intention towards newly evolving technologies.

Perceived risk that was a major concern in the study done by Khedmatgozar and Shahnazi (2018) included concern about monetary loss and privacy. It largely contributes to the slowing of internet banking. Likewise, Martins *et al.* (2014) affirm the influence of perceived risk as an experimental factor with mobile payment demonstrating a negative impact on users' attitudes and intentions. This and many more is why, studies such as the above mentioned and several more, call for financial authorities to take necessary measures to address financial security and privacy concerns if they have to see a better level of acceptance of new-age financial technologies.

6. Practical implications

Given the insights from this study, several practical implications can be drawn for Fintech service providers, emphasizing the role of PU, trust, perceived risk and ease of use:

- Enhancing user trust: creditors should ensure that appropriate safeguards are put in place; clear information about data processing is disclosed, as well as a strong customer service is offered to improve the confidence placed in Robo-advisors. To reduce perceived risks, it is possible to ensure the usage of such approaches as the offer of free trials of products, friendly interface, information presentations of its services and educational programmes. For example, elaboration of measures and safeguards regarding the privacy and securing of the users' data remove such issues. In his research, Eren (2021) has pointed out that the lack of trust and insecurity were among the key concerns highlighted by earlier authors in this respect while Bansal *et al.* (2010).
- Improving ease of use: since the level of PEOU has a direct effect on the attitudes and behavioural intentions towards using Robo-advisors, service providers should

strive to enhance the ease-of-use of their platforms. This pertains to the interface where the organization ensures the customer has an easy time navigating through the system and there is as little learning needed as possible. Another advantage of the current technology is that it is easy to use, and if providers manage to make it even less demanding, the satisfaction and overall utilization will go up. This was also noted by Davis (1989) and was complemented by evidence retrieved from research by Hu *et al.* (2019) as well as Suryono *et al.* (2020).

- Targeted marketing for gender differences: understanding gender differences in the usage of Fintech technology use the multi-group analysis; the providers of such financier technology should approach the market segmentation differentials. For instance, they could create remarks like security for women or financial tips and tricks is our priority, thus creating segments focusing on female users. Hence, above all, offering educational materials that focus on confidence-building regarding market investments among females will also contribute to the uptake of innovations. Other researchers have also recommended that gender differences must be taken into account while strategizing for technology adoption; authors such as Venkatesh *et al.* (2003) and Chawla and Joshi (2018).
- Leveraging SI: to the extent that SI was not established as a significant factor in this study, Fintech providers could perhaps look at how they can increase the usefulness of this influence in the future. Referral sales, rewarding existing clients to encourage them to invite other clients, and partnering with notable clients of the services or popular organizations are some ways to popularize RASs. Also, using social proof like customer reviews and references, case studies and success stories, to make the word about, helps in gaining that much-needed trust. In the previous research studies of Koenig-Lewis *et al.* (2015) and Singh and Kaur (2017), it becomes apparent that SI can also play a role in the case of technology adoption.
- Using AI for personalized services: it can thus be well-concluded that the possibilities for AI-based innovations in financial services are immense. When it comes to the use of AI in service provision, service providers can benefit from using AI in traits such as recommendation systems, portfolio updates on demand and risk evaluations to improve user experiences as well as service delivery. In this way, providing financial advice through AI methods means that the providers are in a better place to provide their users with a satisfactory service by offering advice that meets their needs closely. In line with previous findings by Manser Payne *et al.* (2021) and Liu *et al.* (2023), the use of AI was enhancing financial services.
- Addressing perceived risk: consequently, to eliminate the negative perceptions of risk in regard to the attitudes users have towards Robo-advisors, service providers should ensure they work towards strengthening the security measures in place as well as make them easily comprehensible by the users. This comprises integrated encryption techniques, periodic assessment of security measures and ensuring patrons give their informed consent on the procedures taken to enhance their privacy. However, insurance or guarantees concerning monetary claims that users can experience in relation to the internet are also critical factors that can influence the decision in favour of adoption. The studies of Khedmatgozar and Shahnazi (2018) and Marakarkandy *et al.* (2017) also highlight the importance of perceived risk towards the adoption of financial technologies.

7. Limitations and future research

The cautious generalizations and other methodological limitations are also the main implications of the study. Specifically, the study with nonprobabilistic sampling and having investigated only gender variables restricts the conclusion generalizability. These limitations can be avoided in future studies by using probabilistic sampling techniques and modelling more than one demographic variable as the moderator. Moreover, the study recommends that other factors like prior experience and situational characteristics should be taken into account in future research in designing the relationship between attitude and behavioural intention. There are several areas of concern, which include failure to compare the level of difficulty and quality in accessing and engaging service providers. Although this dimension is recognized as indispensable it has not been in the focus of our current study. Future research should investigate this aspect to gain a better perspective on their influence, hence fill this gap and go further in building on the current literature.

In conclusion, answering the research questions based on the implications of the above paragraphs, it can be suggested that trust, perceived risks, ease of use and demographic variables are critical in RAS adoption. The limitation also outlined in the study reveals the need for subsequent studies to incorporate these factors and examine other control variables that could affect the behaviour of consumers in embracing technology.

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Corresponding author
Sandeep Singh can be contacted at: sandeepsingh1142@gmail.com