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INVESTIGATING THE IMPACT OF FINANCIAL ROBO-ADVISOR ON THE INVESTMENT DECISION-MAKING

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Abstract

This study aims to investigate the influence of different facilitators and Inhibitors on the behaviour intention (BI) to use a financial Robo-advisor and consequently its impact on the investment decision-making. The study proposed Trust and technology self-efficacy as facilitator and complexity and perceived risk as inhibitors that can impact BI to use a robo-advisor. Furthermore, the study also proposed Financial Literacy as a moderator between the relationship of BI and investment decision-making. Collected valid responses were analysed using structure equation modelling by using Smart PLS 4 to evaluate the hypotheses. The discovery of the present study indicated that the facilitator and inhibitor factors have a significant influence on BI and BI on investment decision-making. Moreover, financial literacy has a significant moderating impact on the relationship between BI and investment decision making.

Keywords: Financial Robo-advisor, Financial Literacy, Dual factor theory, Adoption Intension

Introduction

Technology innovation has been the driving force behind the significant development of the financial services sector in recent years (Arjunwadkar, 2018). The emergence of automated robo-advisors and algorithm-driven platforms that provide financial planning services with minimal human intervention is one of the most significant shifts. Robo-advisors are online platforms that use information technology to guide clients through an automated (investment) advisory process. They have sophisticated and interactive user assistance components (Maedche et al., 2016). The finance sector has been embracing new technologies at a rapid pace and plans to invest more in artificial intelligence (AI) than any other industry (Zhang & Fan, 2021). Nowadays, the term "robo-advisor" is almost solely used in reference to financial investment advice, as robo-advisory gradually takes over the traditional retail customer advisory process (Jung et al., 2018). In light of the client evaluation, robo-advisors expand on current advising solutions since their goal is to convert the entire traditional, human-to-human advice process into a digital, human-to-computer procedure (Zhu et al., 2023). Robo-advisors, which provide a fully automated investment experience to a diverse range of potential consumers, entered the market with the development of algorithmic trading, growing e-commerce, and rapid digitization (Dominik Jung, Verena Dorner, 2017; Jung et al., 2018). Robo-advisors provide affordable, individualized financial advice, portfolio management, and retirement planning by utilizing AI, machine learning (ML), and big data analytics (Rossi & Utkus, 2021). Understanding the factors influencing individuals' intention to use robo-advisors is crucial for adoption of robo-advisor in finance sector. According to Zhang et al. (2021), several factors significantly influence consumers' tendency to interact with these platforms. Therefore, a thorough usage model for financial robo-advisors is required to close the current gap in the literature and assist investors in replacing the conventional human-to-human advice procedure (Shahbaz et al., 2019).

Notion of this emergence in finance industry encourages the scholar to empirically examine the facilitators of robo-advisors whereas, the obstructors are remained unfocused in prior literature. Moreover, previous studies focused on Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Hui-Chung et al., 2023; Roh et al., 2023). UTAUT is a widely used model for predicting technology acceptance however these theories mainly focuses on adoption (Shahbaz et al., 2021) which leaves a major gap in literature. To fill the void in existing literature present study incorporated the dual-factor model that enforces the inhibitors and facilitators of technology. This study also considers financial literacy as a moderator in proposed model to address most important problem of investors of developing countries such as Pakistan. While UTAUT is useful for understanding basic drivers of technology use and mostly focused on positive drivers, the dual-factor model is more appropriate for studying robo-advisor adoption because it captures both sides of users behavior. Both aspects are important for investor's intention to use robo-advisor (Singh & Karamcheti, 2025). Present study investigates the user's trust and self-efficacy for utilizing robo-advisors as facilitators of technology whereas complexity and perceived risk of robo-advisors act as inhibitors of technology. The gap between the potential benefits of financial robo-advisors and their low-geared and delayed usage offers academics a great chance to understand how robo-advisors can be used in the financial industry.

The theoretical framework and research approach for this study's analysis of facilitators and inhibitors are described in the following section. The findings from data analysis utilizing models of structural equations and discussions are presented in part four, while section three discusses the study methodologies. The final section brings the overall findings to a close. Our study has theoretical and practical implications in addition to its research constraints.

Literature and hypothesis development

This section relevant previous research and theories in relation to the employment of robo-advisor in financial sector and how different aspects affect user's intention to use robo-advisor.

Trust

Trust is the belief that someone or something is trustworthy, honest, and will fulfil their commitments (Hawley, 2014). The use of robo-advisor depends on users having faith in the technology, data security, and moral behaviour of the service (Dariusz Piotrowski, 2023). Trust plays a crucial role in both predicting user's behaviour and serving as a selection criterion (Jung et al., 2018). In the era of modern technologies, role of trust is becoming more important. The financial industry's continuous transition from "human-to-human" to "human-to-machine" connections begs the question of how trust can be established in a setting that relies heavily on machines (Nourallah et al., 2023). Users could be hesitant to invest without trust, and the system's reputation might take a hit (Habib et al., 2012). In the previous literature, many studies concluded trust is a critical factor that influence investor intension to use robo-advisor for several reasons such as financial security, data privacy, algorithm transparency, trust on vendors (Parashar et al., 2024). Prior literature on robo-advisor and its usage intention has not emphasized how users' long-term trust and loyalty to the platform are influenced by ongoing transparency and hybrid models, as well as how various demographic groups view and build trust in robo-advisor. It hasn't been thoroughly investigated how regulations and user trust in robo-advisors interact, especially how various legal structures affect user confidence. Investors will be more reliable on robo-advisor if they have trust on mechanism (Zhu et al., 2024). Studies concluded that trust is a significant predictor in adoption of robo-advisor (Pokhrel, 2024). Therefore, present study hypothesized that:

H1: Trust has a significant relationship with BIs to use robo-advisor

Technology Self-Efficacy

Self-efficacy is the belief in one's own ability to plan and carry out the actions necessary to achieve specific goals (Song & Thompson, 2011). Bandura, (2011) believed that self-efficacy is the belief in one's own ability to accomplish ongoing tasks and that it is solely dependent on one's own self-confidence and self-assessment. Technology self-efficacy in the context of robo-advisor have an impact on a user's level of comfort and confidence when using a robo-advisor to make financial decisions (Roongruangsee & Patterson, 2024). Higher computer self-efficacy and a lower degree of fatigue were a result of higher intention to use robo-advisor (M Salanova, 2000). Ongoing changes in computer technologies have meant that the existing measures of computer self-efficacy may be outdated (Conrad & Munro, 2008). In the previous literature, researchers are more focused on technology self-efficacy areas like education (Nordlo & Hall-stro, 2019), healthcare (Commons, 2012), and business (Taylor et al., n.d.), other domains, such as personal finance, social media, or smart home technologies are still not well understood (Gavin Cassar, 2009) shown that self-efficacy tends to change depending upon the domain. High levels of self-efficacy are necessary for people to make decisions when dealing with complex financial items (Chung & Lin, 2023.) Higher self-efficacy users might be more proactive with the robo-advisor's features, use advanced functions, and make portfolio adjustments (Al-mutairi, 2023). The study proposes that technology self-efficacy is crucial for understanding and in adoption of robo-advisor.
H2: Technology self-efficacy has a significant relationship with BIs to use robo-advisor

Complexity

Complexity in a robo-advisor refers to the degree of complication and depth present in the financial models, algorithms, and services that the robo-advisor offers (Hodge et al., 2020). The effort required to complete the investment management task determines the task's complexity. The intention to use the robo-advisor decreases as the task's anticipated complexity increases (Rühr et al., 2019). According to Hodge et al. (2020), one of the primary factors influencing perceived task complexity is the necessary actions and, consequently, the effort needed to complete a task correctly. In previous literature studies more focused on acceptance of robo-advisor instead of reducing complexity that will affect the intention to use robo-advisor. There has been relatively little attention paid to how lowering system complexity can directly impact users' intention to use robo-advisor. Robo-advisor system complexity provide plenty of opportunities for better user experience, flexibility, performance, and efficiency (Pokhrel, 2024). Complexity is not a weakness; rather, it may be used to build faster, more intelligent, and more flexible systems that meet changing user demands (Benbya & McKelvey, 2006). Filling these gaps can contribute to the development of robo-advisor systems that are more dependable, transparent, and easy to use while making sure that backend complexity is properly managed to promote long-term success (Rühr et al., 2019).The study proposes complexity in robo-advisor system leads to more efficient and transparent software at the same time complexity in financial algorithms require more efforts of user which influence intension to use robo-advisor.

H3: Complexity negatively affects the BI to use robo-Advisor

Perceived Risk

Risk is stated as the "uncertainties" and the "possibility of loss hinerence" (Radonich & Consulting, 2006). Investors consider risk significantly while making decisions, particularly when it comes to high-stakes financial investments like the cost of their time and money. (Zhu et al., 2024). The robo-advisor's performance is largely dependent on how well it can determine the investor's risk tolerance (Alsabah et al., 2019). Investors subjective assessment of risk, which may be triggered during their engagement with the robo-advisor service, is linked to perceived risk (Zhu et al., 2024). In our context customer perceived risk is financial risk of investors. Financial risks still exist when using automated solutions. First, it demonstrated that there is no assurance that using FRAs will result in favourable financial outcomes; in other words, financial risk does exist (Abraham & Schmukler, 2019). Robo-advisor mostly depend on platforms and technology due to any issue in software may cause of data breaches or cyber-attacks which increases financial risk (Ali et al., 2024). As robo-advisor depends on technology due to which system mostly consider regular market conditions, at times of high instability or extreme market events it may provide false advice to investors due to dependency on platforms and technology (Juan Luis Perez, 2024).The previous literature has provided evidence of Using robo-advisors increases financial risk because of a number of reasons, including algorithmic limits, a lack of human judgment, potential mismatch of risk tolerance, model flaws, and exposure to cyber security risks (Paolo Giudici, 2018; Schwab2, 2024). Additional research in these areas may aid in improving the robo-advisor sector.

H4: Financial Risk has a significant relationship with BIs to use robo Advisor

Behavioural intention to use Robo-advisor

An individual's desire or ability to use a system or technology is known as their behavioural intention (Shahira El Alfy, 2017). Whether or not future users will depend on financial robo-advisors often is strongly influenced by their behavioural intention (Heidari, 2024). Robo-advisors are categorised by the investor's requirement of investment decisions such as low investment, high real-time activity to the market situation or cost-effective investment decision (Mohapatra et al., 2025). Investors can make significant and real time investment decisions through robo-advisors by analysing the current scenarios of market whereas traditional investments take time and increase the risk of loss (Zhang et al., 2021). Mohapatra et al. (2025) concluded that investment decisions through robo-advisors makes the process transparent, efficient and more sustainable as compare to the human advisors which underpins the importance of robo-advisors in todays market. Moreover, investors' intention become more significant to use robo-advisors when robo-advisors provide more nuanced and profound investment portfolios than humans (Seiler & Fanenbruck, 2021). Therefore, present study hypothesized that:

H5: Behavioural intension to use robo-advisor has a significant relationship with Investment decision making.

Financial Literacy

Financial literacy, another term for financial knowledge, includes an essential understanding of the economy and how households make financial decisions in light of the shifting economic landscape (Yi et al., 2023). Financial literacy is the capacity to make wise effective judgments about one's own financial affairs, as well as the knowledge and comprehension of a variety of financial ideas (Hung et al., 2009). User imagination and financial literacy is the main driver of robot advisor acceptance, although financial literacy is crucial for encouraging an investing attitude (Carmem Teresa Pereira Leal, 2024). Individual should be able to understand basic financial terms and current market condition to avoid financial risk (Cui Ling Song, 2023). The previous literature has provided the evidence that investors with better understanding of financial knowledge are liable to seek out the better services of Financial Robo Advisor (Choo et al., 2023). There is insufficient research on how regulatory agencies should take users' differing financial literacy levels into consideration when enforcing laws pertaining to robo-advisors and how literacy affects behavioural intension to use robo-advisor and decision-making. By addressing the gap of financial literacy investor able to lead to better financial outcomes and preventing himself from financial loss (Series, 2013).

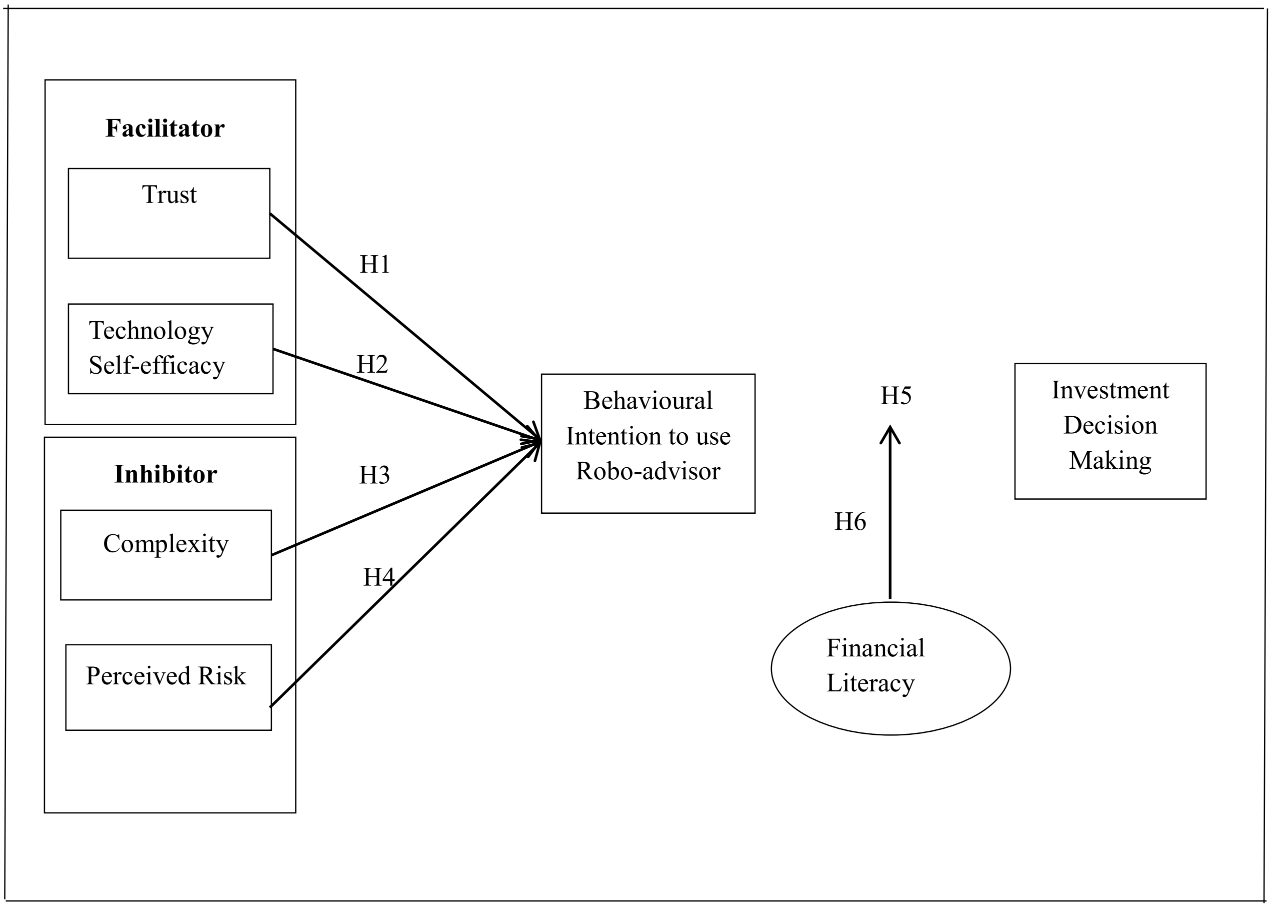
H6: Financial Literacy has a significant moderating impact between the relationship of BI to use robo-advisor and Investment decision making.

Methodology

This section describes the methodology followed by this study.

Development of Measures

After examining the context used in previous studies, we applied the same measures to maintain their content validity. 5-point Likert scale is adopted where 1 is for strongly disagreed and 5 is for strongly agreed. The 3 items scale of trust in technologies is adapted from (Cheng et al., 2019), the 6 items scale of technology self-efficacy adapted from (Asio & Gadia, 2024), the 5 items scale of financial risk is adapted from (Nourallah et al., 2023), the 4 items scale of the complexity is adapted from (Moore & Benbasat, 1991), the 3 items scale of behavioural intension to use is adapted from (Venkatesh et al., 2000), and the 8 items scale of financial literacy adapted from (Mudzingiri et al., 2018) and 6 items scale of the investment decision making was adapted from (Ulfa et al., 2023).



Sampling and data collection

To measure the proposed model, the researchers used a questionnaire-based survey. Up until now, researchers have mostly used surveys to investigate users' decision-making about technology (Viswanath Venkatesh, Michael G. Morris, 2003). All investors, both current and future, from Pakistan Stock Exchange in Karachi, Lahore and Islamabad were chosen using convenience sampling.

A survey can use convenience sampling when it's easy for researchers to reach the participants. Data is collected in the same manner online, allowing all surveys to remain consistent. The online survey ensures research consistency with data collection. Out of the 400 surveys that were sent out, 224 were chosen for analysis after those with biased answers and missing values were eliminated.

Demographics of respondents

Table 1 presents the participant demographics and describe that 57.1% of the participants are male, and 42.0% are between the ages of 35–45 years. Most of the participants have advanced degrees, i.e., 48.7% are graduates, and 45.1% are postgraduates. As a result, our volunteers were well-educated and youthful. In addition, the research took age, education, and gender into account as control variables; all of these factors are insignificant.

Common method bias

Common method bias (CMB) occurs when information is gathered simultaneously from a single source. CMB is a significant problem that needs to be addressed (Podsakoff et al., 2003).In order to confirm that there was no CMB, we employed Harman's single factor test. After categorizing the factors into seven subgroups the first factor explained 34.63% of variance which is below the threshold of 40%. The aforementioned findings demonstrated that CMB is not a problem in this research. Furthermore, only Harman’s single factor test is not sufficient to determine the CMB, therefore, the study used inner variance inflation factor (VIF) to check the CMB. The results of inner VIF are ranging from 1.009 to 1.329 which are below the 3.3 (Kock, 2015), therefore, it is concluded that CMB is not a significant issue in this research.

Table 1. Demographic variables.

Category		Frequency	Percentage
Gender	Male	128	57.1
	Female	96	42.9
	Total	224	100.0
Age	18-25	29	12.9
	25-35	89	39.7
	35-45	94	42.0
	45 and above	12	5.4
	Total	224	100.0
Education	High School	4	1.8
	Bachelor	109	48.7
	Master	101	45.1
	Doctoral	10	4.5
	Total	224	100.0

Results

To evaluate the assumptions, Smart-PLS v4 was utilized to apply partial least squares-structural equation modelling (PLS-SEM). Partial Least Squares Structural Equation Modelling (PLS-SEM) is widely recognized for its effectiveness in evaluating path models with latent variables and their relationships (M. Sarstedt & Liu, 2024). The current study applied the consistent PLS algorithm to ensure robust and reliable model estimation. The next sections present the results from the measurement and structural models.

Measurement model

The research was conducted using the methodology suggested by (HairJF, AndersonRE, TathamRL, 1998). to assess the discriminant, convergent, and content validity of the measurement model.

A review of the appropriate literature and the instrument's pilot study is necessary to ensure content validity. In order to obtain convergent validity, factor loading, Cronbach's alpha, composite reliability (CR), and the average variance extracted (AVE) were examined.

Table 2 shows the results and indicates that all of the items have factor loadings above 0.7, which is acceptable. Cronbach's alpha, AVE, and CR have respective threshold values of 0.70, 0.50, and 0.70 (HairJF, BlackWC, BabinBJ, 2010). All of the Cronbach's alpha, AVE, and CR scores are higher than the thresholds. As a result, convergent validity is unproblematic.

Table2.Results of factor loadings, Cronbach's alpha, CR, and AVE.

Constructs	Items	Loadings	Cronbach's Alpha	CR	AVE
Trust in Technologies	TT1	0.895	0.836	0.902	0.755
	TT2	0.900			
	TT3	0.808			
Technology Self Efficacy	SE1	0.829	0.936	0.950	0.759
	SE2	0.918			
	SE3	0.860			
	SE4	0.833			
	SE5	0.919			
	SE6	0.862			
Financial Risk	FR1	0.871	0.944	0.957	0.818
	FR2	0.918			
	FR3	0.884			
	FR4	0.922			
	FR5	0.924			
Complexity	CLX1	0.856	0.903	0.933	0.776
	CLX2	0.910			
	CLX3	0.911			
	CLX4	0.844			
Behavioural Intension to Use	BI1	0.933	0.910	0.943	0.847
	BI2	0.936			
	BI3	0.892			
Financial Literacy	FL1	0.937	0.984	0.986	0.896
	FL2	0.932			
	FL3	0.956			
	FL4	0.962			
	FL5	0.938			
	FL6	0.930			
	FL7	0.956			
	FL8	0.962			
Investment Decision Making	IDM1	0.925	0.966	0.973	0.855
	IDM2	0.940			
	IDM3	0.913			
	IDM4	0.923			
	IDM5	0.936			
	IDM6	0.911			

Three methods were used to obtain discriminant validity, as recommended by (Gefen, 2005). The initial method was the correlation between the square root of AVE and the factor correlations, as described by (Larcker, 2016), which is the most effective method for assessing discriminant validity. To verify the correlations, the second method involved examining the item loadings and cross-loadings, and the third involved using the Heterotrait-Monotrait Ratio (HTMT) (Sarstedt et al., 2014).

Table 3 demonstrates that the square root of AVE values is higher than the correlation coefficients between all variables. Second, there is no problem with discriminant validity due to the fact that all associated variables have larger item loadings and cross-loadings than other latent variables.

Table3. Inter-construct correlations and discriminant validity.

	BI	**COML**	**FL**	**FR**	**IDM**	**SE**	**TR**
BI	**0.921**						
COML	0.519	**0.881**					
FL	0.016	0.099	**0.947**				
FR	0.481	0.397	0.108	**0.904**			
IDM	0.433	0.368	0.166	0.377	**0.925**		
SE	0.327	0.239	-0.025	0.249	0.041	**0.871**	
TR	0.348	0.340	-0.035	0.130	0.064	0.280	**0.869**

Discriminant validity is supported by low cross-loadings on other constructs, which are the degree to which a variable loads on its intended construct relative to other constructs. Table 4 represents that each item loading highest on its connected construct and much lower on others is an optimal finding.

Table4. Cross Loadings

	BI	**COML**	**FL**	**FR**	**IDM**	**SE**	**TR**
BI1	**0.933**	0.510	0.043	0.464	0.437	0.319	0.342
BI2	**0.936**	0.448	-0.032	0.427	0.444	0.309	0.335
BI3	**0.892**	0.477	0.036	0.436	0.304	0.270	0.278
COML1	0.429	**0.856**	0.115	0.284	0.299	0.191	0.271
COML2	0.465	**0.910**	0.049	0.392	0.356	0.221	0.278
COML3	0.484	**0.911**	0.066	0.324	0.311	0.257	0.386
COML4	0.450	**0.844**	0.123	0.396	0.330	0.169	0.257
FL1	0.022	0.026	**0.937**	0.141	0.128	-0.032	-0.067
FL2	-0.038	0.101	**0.932**	0.077	0.125	-0.036	-0.066

FL3	-0.013	0.108	**0.956**	0.053	0.151	-0.004	0.020
FL4	0.065	0.121	**0.962**	0.128	0.203	-0.029	-0.030
FL5	0.028	0.028	**0.938**	0.140	0.132	-0.022	-0.071
FL6	-0.045	0.091	**0.930**	0.062	0.117	-0.036	-0.066
FL7	-0.020	0.107	**0.956**	0.055	0.152	-0.013	0.024
FL8	0.070	0.129	**0.962**	0.139	0.203	-0.022	-0.032
FR1	0.405	0.316	0.078	**0.871**	0.299	0.220	0.085
FR2	0.417	0.338	0.111	**0.918**	0.300	0.186	0.120
FR3	0.453	0.395	0.100	**0.884**	0.382	0.268	0.141
FR4	0.415	0.318	0.074	**0.922**	0.274	0.246	0.075
FR5	0.476	0.415	0.121	**0.924**	0.432	0.205	0.156
IDM1	0.411	0.344	0.138	0.331	**0.925**	-0.006	0.013
IDM2	0.419	0.340	0.145	0.360	**0.940**	0.058	0.039
IDM3	0.390	0.339	0.180	0.346	**0.913**	0.072	0.128
IDM4	0.395	0.342	0.140	0.338	**0.923**	-0.014	0.013
IDM5	0.418	0.337	0.151	0.365	**0.936**	0.045	0.041
IDM6	0.369	0.340	0.171	0.351	**0.911**	0.070	0.125
SE1	0.264	0.174	-0.038	0.140	-0.015	**0.829**	0.245
SE2	0.303	0.259	-0.037	0.226	0.043	**0.918**	0.313
SE3	0.286	0.184	0.009	0.282	0.071	**0.860**	0.170
SE4	0.267	0.180	-0.029	0.145	0.000	**0.833**	0.250
SE5	0.302	0.261	-0.041	0.217	0.037	**0.919**	0.312
SE6	0.283	0.183	0.007	0.282	0.069	**0.862**	0.169
TR1	0.323	0.378	-0.101	0.122	0.062	0.250	**0.895**
TR2	0.279	0.328	-0.001	0.126	0.087	0.261	**0.900**
TR3	0.300	0.175	0.020	0.090	0.019	0.219	**0.808**

To define the insensitivity of the Fornell-Larcker and cross loadings techniques, the HTMT ratio criterion was developed. The HTMT, or upper limit, is an assessment of the correlation between factors. For two elements to be easily distinguished, the HTMT should be smaller than 1(Henseler et al., 2025). Table 5 shows that the highest value, 0.572, is below the threshold value and confirms that there was no problem with discriminant validity in this study. All of the results show that there were no problems with content, convergence, or discriminant validity in this study, and the use of the data for the structural model is approved.

Table5. HTMT ratio criterion.

	BI	COML	FL	FR	IDM	SE	TR
BI							
COML	0.572						
FL	0.051	0.104					
FR	0.517	0.426	0.108				
IDM	0.457	0.394	0.164	0.390			
SE	0.352	0.257	0.035	0.263	0.062		
TR	0.395	0.387	0.074	0.144	0.083	0.316	

Structural Model

The relationship between constructs based on standardized pathways was tested using the structural model Smart PLS4.

The t-values, p-values, and path coefficient appear in Table 6. Trust → BI, the path coefficient (β) is 0.166 and the p-value is 0.004 showed a significant relationship between trust and BI. Therefore, we accepted H1. Technology self-efficacy has a positive and significant effect on BI as β = 0.130, p = 0.027. So, the study accepted H2. Complexity β = -0.312, p = 0.000, showed a significant negative effect on BI which means as complexity increase the BI of the user will decrease. Based on the mentioned result the study accepted H3. There is a substantial inverse link between behavioural intention and financial risk β = 0.303, p = 0.000 in a sense that as financial risk decrease the BI of user will increase. Based on the mentioned result the study accepted H4. Behavioural intention has a strong, positive effect on actual investment decision-making, β = 0.410, p = 0.000. So, the study accepted H5.

Table6. SEM hypotheses results.

	Original sample (O)	T statistics	P values
TR -> BI	0.166	2.851	0.004
COML -> BI	-0.312	4.548	0.000
FR -> BI	-0.303	4.448	0.000
SE -> BI	0.130	2.213	0.027
BI -> IDM	0.410	5.471	0.000
FL x BI -> IDM	0.200	2.847	0.004

Moderation effect of financial literacy

The study considered the FL as moderator between the relationship of BI and investment decision making. The results showed that FL positively moderates the relationship between BI and IDM, β = 0.200, p = 0.004, which means as the FL increased that will strengthen the positive relationship between BI and IDM. Therefore, the study accepted H6. Figure 2 also graphically described the moderating impacts of FL.

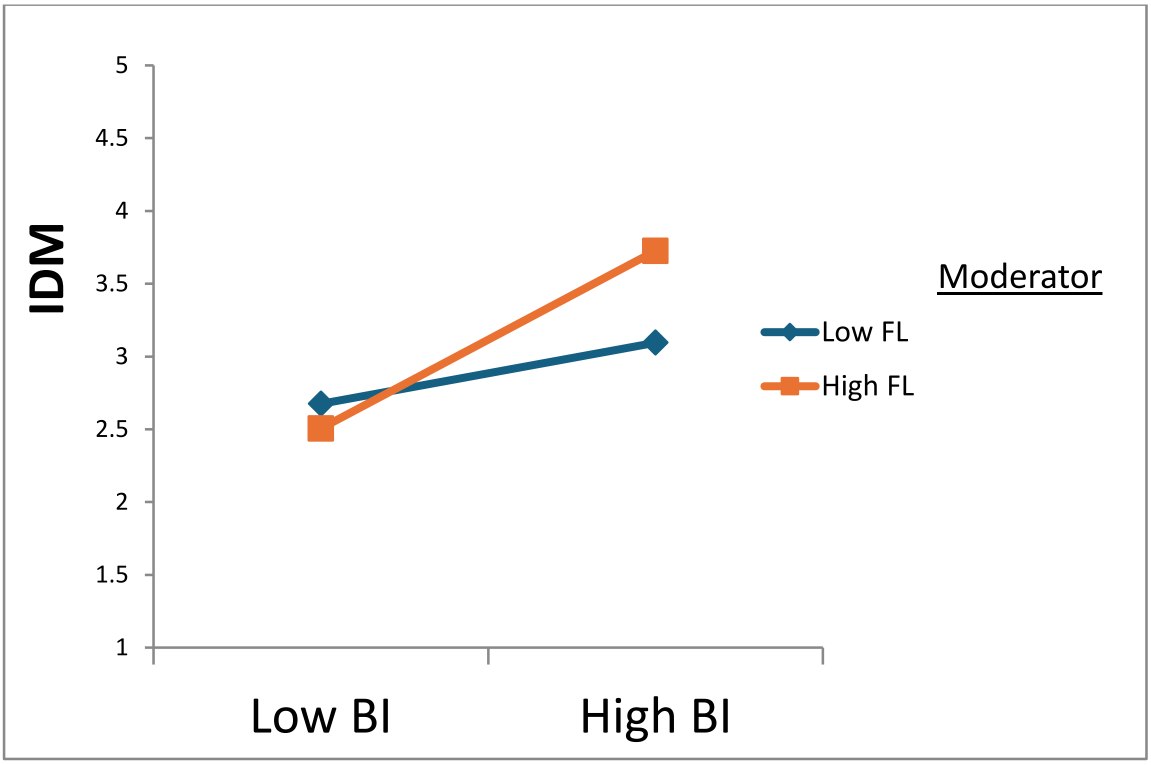


Figure 2: Moderating effects of financial literacy

Furthermore, the results showed 40.8% of the variance in BI, 26.2% of the variance in investment decision making due to the predictor variables.

Discussion

The present study explored the adoption of Financial Robo-Advisors (FRAs) within Pakistan's financial sector, applying the Dual Factor Theory to capture both facilitators (trust, technology self-efficacy) and inhibitors (complexity, perceived risk), with financial literacy as a moderator. The findings revealed several important insights into how these variables interact to influence behavioural intention (BI) and subsequent investment decision-making (IDM).

The analysis shows that trust has a significant positive relationship with behavioural intention ($\beta = 0.166$, $p < 0.01$). This suggests that investors are more likely to use robo-advisors when they believe they are risk-free, accessible and trustworthy. This finding is consistent with prior studies (Cheng et al., 2019; Pokhrel, 2024), reinforcing the idea that trust is foundational in replacing traditional human-to-human advisory with machine-based services.

Similarly, technology self-efficacy also positively affects BI ($\beta = 0.130$, $p < 0.05$). Investors who are confident in their ability to use digital tools and algorithms are more likely to adopt robo-advisors. This aligns with Bandura's self-efficacy theory, suggesting that confidence in technological skills lowers hesitation and enhances proactive financial behaviour (Roongruangsee & Patterson, 2024).

Among inhibitors, complexity ($\beta = 0.312$, $p < 0.001$) and financial risk ($\beta = 0.303$, $p < 0.001$) exert strong negative effects on BI. These findings suggest that when robo-advisors appear overly complicated or when investors perceive high financial risks (such as potential losses or cyber security concerns), their willingness to adopt declines. These results echo the concerns in earlier literature (Alsabah et al., 2019; Rühr et al., 2019) that algorithmic opacity and uncertain outcomes discourage adoption. The results confirm that behavioural intention strongly predicts investment decision-making ($\beta = 0.410$, $p < 0.001$). This implies that once investors form a positive intention to use robo-advisors, they are more likely to make real investment decisions using such platforms. This supports the technology adoption literature that BI is a strong precursor to actual use (Davis, 2000).

The present study result investigates the strong positive relationship between behavioural intention (BI), financial literacy (FL), and investment decision-making (IDM). A moderate predictive performance is indicated by the model's ability to explain 40.8% of the variance in BI and 26.2% in IDM. Financial literacy considerably increases the favourable impact of behavioural intention on investment decisions, as indicated by the interaction term (FL x BI). This implies that having sufficient financial information significantly increases one's ability to make informed decisions, even if they are attracted to invest. In summary, FL is a core competency that also functions as a catalyst to convert intention into sensible, well-informed investing decisions. These results provide validity to the idea that enhancing financial literacy is not only advantageous but also necessary to increase the efficacy of behavioural intentions, which in turn results in more logical and assured investment decisions. In particular, the interaction plot indicates that the impact of BI on IDM is greater among those with higher financial literacy, indicating that when people have a strong behavioural intention to disclose information, they are more likely to be motivated to do so.

Conclusion

Financial robo-advisors are just starting to be taken up by investors in the industry. It is a good time to have or use robo-advisors in the financial sector so that investing can be improved with artificial intelligence and machine learning. It is shown by this study that a few main factors are crucial for the successful adoption of financial robo-advisors. This research supports firms looking to introduce a financial robo-advisor by showing which factors matter most at the start. Another difference with previous research is how this study points out the huge advantage of the Using dual Factor theory to understand intentions to use robo-advisor services. Dual factor theory gives better results when compared to the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). All previous studies focused on adoption examined the TAM model and UTAUT. The researchers also looked at issues that users care about when introducing new technology, including trust and technology self-efficacy. As a result, we see a greater significance in the literature about financial robo-advisor. The territory for our sampling is Pakistan, though it is a developing country. People’s lack of financial knowledge is the main reason why innovative systems are not embraced, both in developing countries and in some developed countries. In our understanding, this study is the first to connect Financial Literacy to the use of Financial Reporting Assignments as a moderator. The result we found helps users to recognize and incorporate this trait when coming to rely on financial robot-advisors

Theoretical Implication

This research adds important information about bringing financial robo-advisors into the market. For the first time, the research provides practical evidence for Financial robo-advisor use in Pakistan. Second, since financial robo-advisor was just being adopted by people in the early stages, earlier studies put more emphasis on its importance and acceptance because risk and complexity were less-studied subjects. Additionally, very little research into financial robo-adoption exists and what studies exist mostly centre on a single aspect or the Dual Factor theory. To our knowledge, this research offers the first Dual Factor theory-based model for understanding behavioural intentions to use robo-advisor. For these reasons, this perspective on Dual Factor theory is a new and welcome addition to the literature on financial robo-advisor adoption. Next, the model took trust in information and how comfortable the patient is with technology to examine their role in behavioural intension. Our results will add to the understanding of trust and technology self-efficacy in research on technology acceptance. Also, the findings on financial literacy help researchers because the current study points out this obstacle to using financial robo-advisors. Using this research can guide other scholarly work and build knowledge about using financial robo-advisors.

Practical Implication

Similar to its theoretical achievements, the study made multiple practical contributions as well. The study's conclusions offer crucial recommendations and significant ramifications for financial robo-advisor practitioners and implementers that can help ensure the product's effective adoption. First, according to the findings, establishing user trust is crucial for adoption; as a result, robo-advisors must incorporate features that improve transparency, dependability, and credibility, like providing an optional human advisor support system and a clear explanation of how investment recommendations are made. Users can feel more competent and in charge by increasing their technology self-efficacy through guided on boarding, instructional resources, and user-friendly interfaces. However, the existence of barriers like perceived complexity and financial risk emphasizes the necessity of streamlining the user experience and effectively conveying risk in a way that is comprehensible and comforting. Third, the moderating influence of financial literacy, which inhibits the adoption of financial robo-advisors in developing nations, is examined in this study. When taken as a whole, these insights help financial technology companies, Pakistan Stock Exchange, Financial Institutions such as banks balance lowering inhibitors and strengthening facilitators, guaranteeing a more user-centric strategy that raises robo-advisory service uptake, trust, and usability

Limitations and future directions

The authors point out a number of challenges faced in this study. In this study, attention is given to the pace of adoption of a financial robo-advisor in Pakistan's financial sector. The absence of human advisory considerations in this research could change the rate of adoption for this type of software. Further studies could use this research model when introducing security risk inhibitors. Because security issues can affect how confident users are in the platform, they make achieving success difficult. This work gave information on the adoption of financial robo-advisors in Pakistan and other developing countries. In order to increase the scope of the study, future scientific work will have to test this model in developed countries, as financial investors have much better financial literacy there. Trying the research model in different cultural scenarios with an emphasis on adoption financial robo-advisor is possible. In order to obtain a more comprehensive understanding of user behaviour in the digital financial landscape, Dual-Factor Theory should be used in combination with more comprehensive models or longitudinal studies, even though it offers a useful framework for identifying adoption drivers and barriers

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