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Determinants Shaping Choices for Robo and Human Advisors in The German Financial Market: The Analysis of Retail Consumers

Akanksha Kumari
HTW DRESDEN, Dresden, Germany
akankshakumari227jsm@gmail.com
Namra Iqbal
National University of Modern Languages, Islamabad, Pakistan
Sadia Fazil
National University of Modern Languages, Islamabad, Pakistan
fazil_sadia@yahoo.com

Corresponding: namraiqbal01@gmail.com

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ABSTRACT

The financial industry has witnessed the emergence of robo-advisory, a Fintech breakthrough resulting from the integration of digitalisation in the era of robo-technology. The adoption of technology and Artificial Intelligence (AI)-based advisors are now becoming common in distinct functions of everyday life. The financial technology market is also heading in the same direction. This research is aimed at performing an analysis of consumer perspectives on the adoption of robo-advisors in the German financial industry. For this purpose, this study intends to investigate the impact of opportunities, and threats on the intention to use robo-advisors by the German retail investors. This study uses cross-sectional data from 145 respondents using an online questionnaire to analyse factors impacting retail consumer decision-making regarding human and robo-financial advisors in Germany. Two step PLS-SEM model is applied to analyse the data. It is concluded that men, younger individuals (aged 18-35 years), those with higher financial literacy (master's degree), and income (more than -500 euros) groups are more likely to invest through robo-advisors. The findings of PLS-SEM show significant positive relation between opportunities and intention to use robo-advisors. The findings further show significant negative relation between threats and intention to use robo-advisors. Robo-advice can contribute to financial inclusion and help financially fewer literate investors to invest in the capital markets. If the regulators of robo-advisors and robo-advisors themselves can ensure a high degree of precision and suitability for investors, then robo-advice has an enormous potential to balance, irrespective of replacing traditional financial advisors in the future.

INTRODUCTION

The financial industry has witnessed the emergence of robo-advisory, a fintech breakthrough resulting from integrating digitalisation in the era of robo-technology (Chandani, 2022). The development of this technology brings about a shift in the traditional advisory model (Hakizimana et al., 2023), which in turn attracts new customers and creates new demands among existing ones (Capponi et al., 2022). Robo-advising offers greater accessibility and affordability than traditional advisory services (Nagadeepa et al., 2023). Traditional advisors have historically focused on wealthier clients, leaving a vacuum for modest savers. This is because traditional advisors believe that the potential earnings from these types of customers are too low (Torno et al., 2021). Robo-advisors are addressing this need by providing financial services to low-income millennials who are originally seen as little savers but have expanded their customer base to include wealthier individuals (Reddavide, 2018). Hwang et al. (2021) explained the working of robo-advisors, which is an internet-based financial platform that provides automated investment advice and utilises algorithms to assess asset allocation and automatically rebalance portfolios for investors. The portfolio of each customer is designed to get the most favourable returns, while considering various risk levels. The key targeted audience of robo-advisors is private investors who frequently rely on their financial judgment or seek investment advice from acquaintances, family members, or online sources. The fundamental concept is to require those investors to complete an online questionnaire. These factors are essential to building a suitable investment portfolio for clients and guaranteeing conformity with rules and regulations (Back et al., 2023).

Germany is a promising market to study this emerging phenomenon. The German savings rate is among the highest in Europe (Šubová et al., 2024), and investors are likely to seek out higher-yielding assets like Exchange Traded Funds (ETFs) due to the country's exceptionally low interest rates (Ilmanen, 2022). In light of these trends, researchers want to know how open German investors are to the idea of working with a robo-advisor rather than a human advisor (Atwal & Bryson, 2021). Therefore, this research aims to analyze consumer perspectives on the adoption of robo-advisors in the German financial industry, which is classified as disruptive innovation.To fulfil this aim, this study investigates the impact of opportunities and threats on the intention to use robo-advisors of German retail investors.

The key objective of the study is to assess the factors affecting the decisions of retail consumers to select robo-advisors over human financial advisors in Germany. The sub-objectives of this study are:

- To identify the major opportunities retail banking consumers, face when selecting robo-advisors
- To identify the major threats retail banking consumers, face when selecting robo-advisors

Robo-advisors must provide unambiguous and comprehensive details on their algorithms, fees, investing strategies, and associated threats (Cardillo & Chiappini, 2024; Lam & Swensen, 2016). Customers should possess an in-depth understanding of the manner in which their finances are being handled (Shiva et al., 2023). Similarly, customers want reassurance regarding the security of their personal and financial information (Capponi et al., 2022). Robo-advisors must implement strong information and security measures to safeguard sensitive data from unauthorised access or breaches (Bhatia et al., 2021). Although attempts have been made to simplify the investment procedure, certain clients may perceive the notion of robo-advise as daunting or too intricate, especially those with low financing literacy (Back et al., 2023; Kramer, 2016).

The study provides insights into the evolving landscape of financial advisory services in the German Fintech market, where the preference is given to robo-advisors. Understanding the consumer perspective is critical for policymakers and service providers in adapting to change consumer preferences. The findings of the study will help to assist the industry stakeholders in catering to the needs of consumers, improving service quality, and driving the growth of robo-advisory platforms. It will also ensure the consumers' financial well-being and trust in technology-driven solutions.

Robo advisors may provide opportunities and attract more investors by providing positive client experiences and ensuring customer trust (Roongruangsee & Patterson, 2023). In contrast, adverse experiences can impede acceptance and erode trust in automated investing solutions. Similarly, evaluating client satisfaction can aid in determining if these platforms adequately meet the requirements of different demographics, especially those historically neglected by conventional financial advisors (Bai, 2024). Customer satisfaction may serve as a crucial distinguishing factor in a competitive industry with many robo-advisor options (Tiberius et al., 2022). Companies that place a high value on user experience and consistently provide opportunities are more expected to attract and maintain a larger number of clients, therefore improving their competitive standing in the market (Pei et al., 2020). In the same way, gaining insights into the impact of threats on the intention to use robo-advisors may impact investment behaviour in the realm of robo-advisors (Bhatia et al., 2020). This can offer significant knowledge for both investors and robo advisors' platforms. Investors may be more likely to use robo-advisors if they see them as having lower risk than conventional investment approaches. Similarly, the credibility and reputation of robo-advising platforms might be influenced by the perceived risk associated with them. Researching this field can provide insights into the variables that shape client needs by providing them with opportunities and the potential consequences of perceived threats on the reputation of robo advisors.

Robo-advisors, which are online platforms powered by artificial intelligence, are progressively gaining a larger portion of the market. However, these relatively recent financial services have not received much research attention (Weber et al., 2023). Limited information exists about the factors that lead certain investors to utilise robo-advice specifically for the critical task of asset allocation (Back et al., 2023). This research aims to address this gap by examining the causal impact of investor behaviour on the likelihood of utilising robo-advice. The existing research on robo-advisory is limited, and there is no widespread agreement about the connection between socio-demographic factors, risk preferences, prior trading experiences, and the inclination to use Fintech and digital financial services (Ansari & Bansal, 2024; Yi et al., 2023). Additional empirical research is needed, with particular emphasis on the economic behaviour of customers (Hentzen et al., 2022). Comin & Mestieri (2014) also highlighted that there is a significant vdeficiency in the existing body of research at the micro level about the use of this technology.

LITERATURE REVIEW

Various research has examined the prevalence of robo-advisors in wealth management compared to the traditional fund sector. The concerned studies of this study are critically reviewed as:

Impact of Opportunities on Intention to Use Robo-Advisors

Baker (2017) discussed that the expansion of robo-advisors requires collaboration across several fields to safeguard the integrity of financial markets. Legal, economic, and behavioural scientists require a comprehensive understanding of data science in order to articulate new regulation tactics. Data scientists must have knowledge of legal frameworks in order to ensure the viability of these tactics. The advantages of these endeavours are expected to surpass the disadvantages, as the identical economies of scale render robo-advisors financially efficient (Cardillo & Chiappini, 2024).

Examining whether or not robo-advisors can fulfil the same fiduciary responsibility as human financial advisors, Clarke (2020) delves into the ways in which these platforms have altered the wealth management landscape. Reduced management fees through passive portfolios, simplified on-boarding procedures, and algorithm-based decisions for investors having less experience and who would not otherwise be eligible for a conventional human financial advisor and are the guiding principles of robo-advisors. Clients may access their portfolios from wherever using mobile devices (Shiva et al., 2023).

Using data from a global three-stage Delphi research (Tiberius et al., 2022), it is predicted that robo-advisor sector is headed in terms of market size, competitiveness, growth drivers, client groups, challenges, services, technology, and social change. According to the findings, the number of robo-advisor services will continue to rise in the financial advisory industry (Arenas-Parra et al., 2024). In light of the above discussion, this study formulates the following hypothesis:

H_1: There is a significant impact of opportunities on the intention to use robo-advisors.

Impact of Threats on Intention to Use Robo-Advisors

Several major investment banks have prioritised the integration of robot advisory services into their wealth management systems as part of their digital transformation initiative (Wewege et al., 2020). However, an imminent challenge for all robo-advisors in the industry is the intense competition they are encountering. Existing literature indicates that a significant number of retail investors lack expertise in making financial decisions, leading them to actively seek financial assistance (Barroso & Laborda, 2022). Young retail investors (YRIs) between the ages of 18 and 29 are prime examples of individuals who actively seek financial guidance due to lack of expertise in making financial decisions (Nourallah et al., 2023). Nevertheless, their constrained financial means may impede their ability to engage the services of human consultants (Siddique et al., 2024). In order to resolve this predicament, YRIs typically seek cost-effective AI-driven automated services, such as financial robo-advisors ((Lusardi et al., 2020). Robo-advisors gather and retain the confidential financial data of their subscribers. Consequently, they become susceptible to cyber-attacks that try to take personal information. Robo-advisors gather and retain confidential financial data about their subscribers (Aw et al., 2024). Consequently, they become susceptible to cyber assaults to steal personal and financial information. Security breaches may result in financial losses for subscribers and harm the brand of the robo-advisor firm. Therefore, the following hypothesis is made:

H_2: There is a significant impact of threats on the intention to use robo-advisors.

RESEARCH METHODOLOGY

The non-probability sampling technique ensures a diverse and representative sample (Saunders et al., 2021). Among the various non-probability sampling techniques, this study explicitly follows the purposive sampling technique. This technique involves purposefully selecting participants based on specific criteria related to the aims of this study (Saunders et al., 2021). In this research study, the sampling strategy targets German financial market retail consumers with experience with humans and robo-advisors. The purposive sampling technique helps select intentional and focused participants possessing valuable perspectives and insights about the research (Saunders et al., 2021). This research aims to collect in-depth information related to the factors impacting the decisions in the financial advisory domain by targeting retail investors with experience with not only human but also robo-advisory services. This technique helps researchers strategically select a target population who can reap relevant and rich data, thereby contributing towards a systematic analysis of the factors impacting the choices between human and robo advisors from the perspective of the German financial market. The survey is distributed through LinkedIn, Facebook, and personal contacts within the financial sector and the general public. The questionnaire survey was developed using Google Forms and comprised sections covering demographic information, investment habits, and perceptions regarding robo-advisors. Participants are asked to respond to questions using various response formats, including multiple-choice and a five-point Likert scale, where 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree and 5 = strongly agree.

The survey link is accompanied by a brief introduction explaining the aim of the study and encouraging participation. The survey was launched on January 1, 2024, and remained open for responses until January 20, 2024. This 20-day duration allows for a comprehensive data collection while minimizing respondent fatigue. Key metrics such as response rates, investment behaviours, and participant demographics are tracked throughout the survey period to ensure a representative and engaged sample. Survey questions comprise different sections: demographic questions, robo-advisory questions, dependent variable questions, and independent variables questions. In demographic variables, participants provide information on gender, age, education, and monthly savings. In robo-advisory questions, participants provide information on whether they currently or had previously invested in securities. In addition, participants show their involvement with robo-advisors, including the frequency of buying and selling securities through robo-advisors. Reasons for choosing robo-advisors are also explored. The intention to use robo-advisors is measured using six survey items: I1, I2, T1, T2, T3, and T4. These survey items enquire about the intention to use robo-advisor in the future, the expectation of using robo-advisor in the following 6 months, the intention to disclose sensitive and personal information to robo-advisors, the consideration of robo-advisors as trustworthy, trust in the information and portfolios suggested by robo-advisor and willingness to take a risk when investing in securities using robo-advisors (Venkatesh et al., 2003, 2012; Zhou et al., 2019). The opportunities are measured using eight survey items: O1, O2, O3, O4, S1, S2, S3, and S4. These survey items enquire about the advantages of robo-advisors in making financial decisions, the use of robo-advisors to enhance the probability of attaining things useful, increasing financial profitability using robo-advisors, completion of financial goals quickly, clear interaction with robo-advisors, easy to use robo-advisors, learning with robo-advisors, and becoming skilful using robo-advisors (Moore & Benbasat, 1991; Venkatesh et al., 2003, 2012). The threats are measured using three survey items: TH1, TH2, and TH3. The survey items enquire about the consideration of robo-advisors as a threat instead of a chance to prevailing businesses, the perceived risk coupled with robo-advisors and its impacts on future use, and the fear of losing money using robo-advisors.

The survey items are randomly named to avoid common effect bias from the questionnaire and analysis is made using PLS-SEM model. Structural Equation Modelling (SEM) with Partial Least Square (PLS) is a complex approach of SEM, which uses PLS as a method for estimation (Wong, 2013). The PLS-SEM has two steps: The first step involves the validity and reliability of the measurement model (AlMulhim, 2021). The validity and reliability measures cover factor loading, convergent validity, construct validity, discriminant validity, internal reliability, and composite (AlMulhim, 2021). The next step is to examine the hypotheses and assess the model's predictive power (Hair et al., 2019). PLS-SEM has benefits and applications measured through Smart PLS compared to SEM based on the covariance method reported from AMOS graphics. PLS-SEM is a superior method to covariance-based SEM as this model measures the entire model instead of splitting it into components (Alhumaid & AAssali, 2023). This method is appropriate when the path model has formative observed items (Sari & Kanegae, 2020). In case of a problem with data distribution, the researcher requires a latent variable score for further analysis, and PLS-SEM is helpful in that case, too (Hair et al., 2019). It appropriately predicts factors, unobserved factor preclusion, and application of theory development (Hair et al., 2019). The SmartPLS version 4 is utilized for SEM-PLS modelling.

Participants are given information about the purpose of the study, and voluntary consent is acquired before proceeding with the survey. Anonymity and confidentiality of responses are emphasized, and participants ensure that the use of their data will be restricted solely for research (Saunders et al., 2021). Participants are informed about their voluntary participation in the research process and that they are not forced to become part of the survey. In addition, the researcher remains impartial from the research participants and withholds the biases by considering about 10 percent of anonymous respondents (Saunders et al., 2021).

RESULT AND DISCUSSION

Descriptive Analysis

The descriptive analysis describes the key features of the dataset to identify trends and patterns within the dataset. The result of descriptive statistics in Table 1 shows mean of all constructs near to 3 which means neutral.

Table 1: Descriptive statistics

	N	Mean	Std. Deviation
	Statistic	Statistic	Statistic
I1	145	3.14	1.136
I2	145	2.77	1.286
T1	145	2.65	1.357
T2	145	2.94	1.171
T3	145	2.99	1.155
T4	145	2.93	1.206
S1	145	3.10	1.145
S2	145	3.30	1.120
S3	145	3.46	1.118
S4	145	3.30	1.186
O1	145	3.26	1.098
O2	145	3.27	1.126
O3	145	3.19	1.168
O4	145	3.06	1.153
TH1	145	2.57	1.091
TH2	145	2.99	1.024
TH3	145	2.75	1.044

Considering the perspective of investment in securities (shares, bonds, funds, ETFs, ETCs), 81 respondents covering 55.9% of the sample invest in securities and 64 respondents covering 44.1% of the sample do not invest in securities as shown in Table 2. Considering the perspective of investment in securities (shares, bonds, funds, ETFs, ETCs) in past, 91 respondents covering 62.8% of the sample had invested in securities and 54 respondents covering 37.2% of the sample had not invested in securities as shown in table 2.

Table 2: Investment in securities

	Do you invest in securities?		Had you invested in securities?	
	Frequency	Percent	Frequency	Percent
Yes	81	55.9	91	62.8
No	64	44.1	54	37.2

Considering the perspective of the frequency of buying securities, 69 of the respondents invest less than once per year in the securities covering 47.6% of the sample. 14 respondents invest 1 time per year in the securities covering 9.7% of the sample. Moreover, 24 respondents invest 2-6 times per year in securities covering 16.6% of the sample. Furthermore, 20 respondents invest 7-12 times per year in securities covering 13.8% of the sample. In addition, 14 respondents invest more than 24 times per year in the securities covering 9.7% of the sample. However, only 4 respondents invest every day in the securities covering 2.8% of the sample as shown in Table 3.

Table 3: Frequency of trading securities

	How often do you buy securities?		How often do you sell securities?	
	Frequency	Percent	Frequency	Percent
Less than once per year	69	47.6	90	62.1
1 time per year	14	9.7	17	11.7
2-6 times per year	24	16.6	20	13.8
7-12 times per year	20	13.8	9	6.2
More than 24 times per year	14	9.7	6	4.1
Everyday	4	2.8	3	2.1

Considering the perspective of the frequency of selling securities, 90 respondents sell less than once per year in the securities covering 62.1% of the sample. 17 respondents sell 1 time per year in the securities covering 11.7% of the sample. Moreover, 20 respondents sell 2-6 times per year in the securities covering 13.8% of the sample. Furthermore, 9 respondents sell 7-12 times per year in the securities covering 6.2% of the sample. In addition, 6 respondents sell more than 24 times per year in the securities covering 4.1% of the sample. However, only 3 respondents sell every day in the securities covering 2.1% of the sample as shown in table 4.

Table 4: What is the reason for your choice of robo-advisors?

	Frequency	Percent
Comfortable	38	26.2
I prefer making my own analysis	50	34.5
I rely on recommendations from others	25	17.2
Other	32	22.1
Total	145	100.0

Considering the perspective of the research for the choice of robo-advisors, 38 respondents feel robo-advisors comfortable covering 26.2% of the sample. Moreover, 50 respondents feel that robo-advisors are preferable for making their own analysis, which covers 34.5% of the sample. In addition, 25 respondents feel that robo-advisors are preferable as they rely on recommendations from others, which cover 34.5% of the sample. Lastly, 32 respondents feel robo-advisors are preferable for other reasons covering 22.1% of the population as shown in Table 5.

Table 5: Robo-Advisory and Demographics

Gender	Robo-Advisory Investment		Age	Robo-Advisory Investment		Education	Robo-Advisory Investment		Savings	Robo-Advisory Investment	
	Yes	No		Yes	No		Yes	No		Yes	No
Male	11.0%	47.6%	18-35	13.8%	73.8%	High School	1.4%	1.4%	0	0.7%	2.8%
Female	8.3%	31.0%	36-50	6.2%	4.1%	Bachelor's degree	7.6%	22.1%	Less than 100	0.0%	4.8%
Other	2.1%	0.0%	Over 50	1.4%	0.7%	Master's degree	12.4%	54.5%	100-300	1.4%	18.6%
						Other	0.0%	0.7%	301-500	1.4%	10.3%
									501-1000	6.2%	18.6%
									1001-5000	6.9%	18.6%
									More than 5001	4.8%	4.8%

The demographics are assessed in the context of investment via robo-advisory as shown in table 5. For gender, the results reveal that 11% of males and 8% of females invest via robo-advisors. In the context of gender, the results reveal that about 14% of investors belong to the age bracket of 18-35 years, 6% of investors belong to the age bracket of 36-50, and 1.4% of investors belong to the age bracket of 50+ years who invest via robo-advisors. For education, the results reveal that about 1.4% of investors belonging to high school, about 8% of investors having bachelor's degrees, and about 12% of investors having master's degrees invest via robo-advisors. In the context of savings, about 1% of investors have no savings, having savings of about 100-300 euros, and have savings of about 301-500 euros invest via robo-advisors. About 6% of investors have 501-1 000 euros savings, 7% of investors have 501-1 000 euros savings and about 5% of investors having more than 5 001 euros savings invest via robo-advisors. These results reveal that men, young, financially literate and higher income saving propensity class invest via robo-advisors. This study uses Smart PLS 4 software to estimate PLS-SEM as shown in Figure 1 for path analysis.

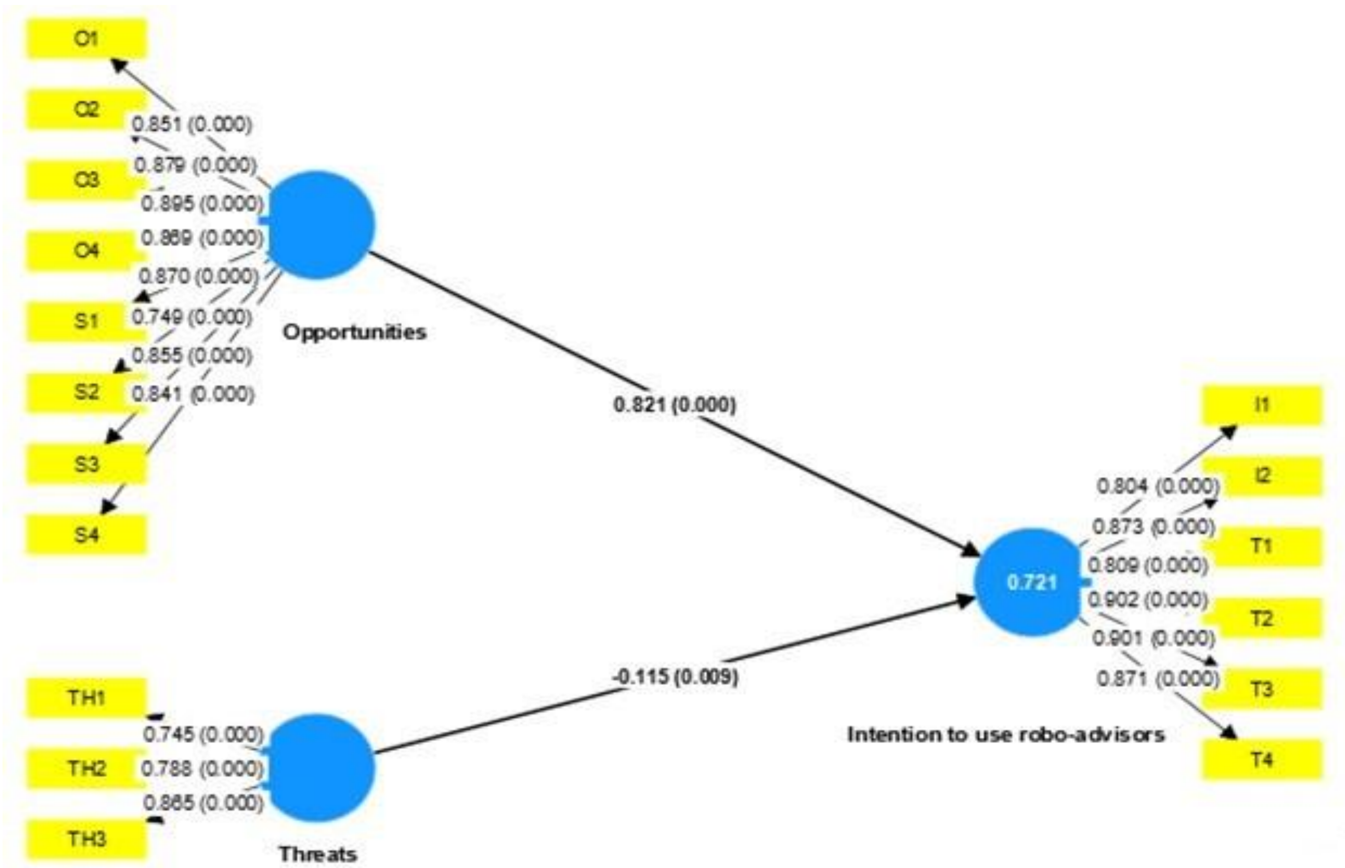

Figure 1: PLS-SEM Model of Study

Measurement Model

Among the types of measurement models: reflexive and formative models, this study uses the reflexive model as the causation goes from latent construct to observed items.

Factor Loading

The threshold to eliminate a factor is 0.7 i.e. a factor having a factor loading of less than 0.7 should be eliminated due to lack of unidimensionality (Awang, 2012). The result of unidimensionality in the measurement model is shown in table 6. It shows the factor loading of more than 0.7. In this way, all three variables (intention to use robo-advisors, opportunities, and threats) have unidimensionality as they meet the threshold criteria with factor loadings of 0.7.

Table 6: Unidimensionality

	Intention to use robo-advisors	Opportunities	Threats
I1	0.804		
I2	0.873		
T1	0.809		
T2	0.902		
T3	0.901		
T4	0.871		
S1		0.851	
S2		0.879	
S3		0.895	
S4		0.889	
O1		0.870	
O2		0.749	
O3		0.855	
O4		0.841	
TH1			0.745
TH2			0.788
TH3			0.805

Validity

Convergent validity.

Average Variance Extracted (AVE) is the measure to calculate validity for all constructs and convergent validity is attained when the variables have an AVE of 0.5 or more (Hair et al., 2019). The results of AVE show that the value of AVE is 0.741 for intention to use robo-advisors, 0.726 for opportunities, and 0.641 fir threats; thereby confirming convergent validity in the variables as these values are greater than threshold values.

Standardized Root Mean Square Residual (SRMR) with zero value shows a perfect fit. It has a threshold value of less than 0.08, which seems to be a generally good fit (Schuberth et al., 2023). The result of SRMR as shown in Table 7 shows the absolute fit model meets the threshold criteria. For the fit indices, another measure is the Normed Fit Index (NFI), which ranges between 0 and 1. A value near to 1 is deemed as a better fit and a threshold value of more than 0.9 seems to be a generally good fit (Schuberth et al., 2023). The result of NFI as shown in Table 7 shows a good fit.

Table 7: Construct validity

Model Fitness	Estimated model
SRMR	0.068
Chi-square	381.130
NFI	0.826

Discriminant validity (HTMT)

The heterotrait-monotrait ratio of correlations (HTMT) assesses discriminant validity in PLS-SEM with a threshold value of less than 0.9 (Hair et al., 2024). The result of discriminant validity is shown in Table 8, which shows the HTMT ratio among all variables meets the threshold criteria; thereby validating the presence of discriminant validity.

Table 8: Discriminant validity

	Intention to use robo-advisors	Opportunities	Threats
Intention to use robo-advisors			
Opportunities	0.889		
Threats	0.295	0.200	

Reliability

Internal reliability.

The measure to assess internal reliability is Cronbach's Alpha with a threshold value ranging 0.70 to 0.95 (Hair et al., 2019). The results show that there is internal reliability among the items of the constructs as shown in Table 9.

Table 9: Internal reliability

	Cronbach's alpha
Intention to use robo-advisors	0.930
Opportunities	0.946
Threats	0.741

Composite reliability.

The composite reliability also assesses internal reliability with a threshold value ranging from 0.70 to 0.95 (Hair et al., 2019). The results show that there is internal reliability among the items of the constructs as shown in Table 10.

Table 10: Composite reliability

	Composite reliability
Intention to use robo-advisors	0.945
Opportunities	0.955
Threats	0.842

All the measures of the measurement model show that the items and their respective constructs are valid and dependable.

Structural Model

The assessment of the structural model requires a preliminary assessment of collinearity statistics using the Variance Inflation Factor (VIF). There is a possible critical concern of collinearity when the value of VIF is equal to and greater than 5. There is a concern of collinearity when the value of VIF is equal to and greater than 3.5. However, the ideal threshold value of VIF is less than 3. The results of VIF are reported in Table 11, which shows the ideal threshold value of collinearity statistics.

Table 11: Regression analysis

	Path coefficients	T statistics	P values	VIF	Hypotheses Testing
Opportunities -> Intention to use robo-advisors	0.821	26.399	0.000	1.034	Accepted
Threats -> Intention to use robo-advisors	-0.115	2.613	0.009	1.034	Accepted
R-square	0.721				
R-square adjusted	0.717				

Once collinearity statistics reveal no correlation, the next step is to measure the structural model for assessment of the relationship between variables. The result of regression analysis in Table 11 shows that the path coefficient of opportunities is 0.821 with a t-statistic of 23.339 (p-value = 0.000). It shows the relationship between opportunities and intention to use robo-advisors is positive and significant at 1%; thereby accepting hypothesis 1. Furthermore, the path coefficient of threats is -0.115 with a t-statistic of 2.613 (p-value = 0.009). It shows the relationship between threats and intention to use robo-advisors is negative yet significant at 1%; thereby accepting hypothesis 3. Table 11 also reports the value of the R-square is 0.721, which shows that the overall model is substantial fit.

Discussion

The results show one-fifth (21%) of the respondents invest via robo-advisors. These results are quite similar to the results of Cedrell and Issa (2018) and in the Swedish financial market where 13% of respondents invest via robo-advisors. Robo-advisors are novel and innovative tool in the financial market of Germany and its adoption is not widespread among the market consumers.

It is concluded that men, younger individuals (aged 18-35 years), those with higher financial literacy (master’s degree), and higher income (more than 500 euros) groups are more likely to invest through robo-advisors. Male users normally have more level of trust in the service use in comparison with female users consistent with the study (Cevey & Ojala Burman, 2019). Therefore, it is significant for robo-advisors to get the adjustment of diverse consumer profiles for personalizing the service and developing the concern of user-friendliness and security.

Other than gender, these results are consistent with the study of Cevey and Ojala Burman (2019), where younger consumers have a higher probability in comparison to older consumers to recommend the robo-advisors to other investors to work digitally and feel contented in making automated investments. The findings are similar to the study of Isaia & Oggero (2022), where the Millennial investors are twice the older investors considering a robo-advisory along with Generation Z being growing up in the technological world and having the probability of seeking finances.

Regarding education, the results reveal that investors having an elevated level of financial literacy increases the probability of using financial technology in their investment plans such as robo-advisors. The result is similar to the empirical researches where scholars confirm that a high degree of education increases the chances of financial investment (Cedrell & Issa, 2018; Cole et al., 2014).

Further, the results show that higher income increases the investment through robo-advisory since income leads to saving propensity, which creates the investment probability. The results are consistent with the study of Cedrell and Issa (2018), which show that the presence of monetary resources increases the probability of saving and investment.

The result of PLS-SEM shows the relationship between opportunities and intention to use robo-advisors is positively significant. The positive as well as significant impact of opportunities on intention to use robo-advisors is well-supported in the empirical research (Bai, 2024; Rossi & Utkus, 2020). The user interface of robo-advisory and ease of use in these platforms significantly impact user satisfaction, which influences the intention to use robo-advisors. The investments made by robo-advisors impact the financial performance of retail investor; thereby augmenting their satisfaction. The efficient management of risk and positive return contributes towards user satisfaction and long-run use of intention to use these services. The robo-advisory services provide opportunities to the investors by focusing on the significance of quick-to-respond customer support. The efficient solution to the problems and effective communication with retail investors positively impact the intention to use such platforms. These platforms also give investors feedback on the opportunities and investment performance for learning in association with an elevated level of satisfaction for continuing the use of robo-advisors for their needs of investment as reported in the result of this study.

The result of PLS-SEM also shows the relation between threats and intention to use robo-advisors is negatively significant. The outcomes are consistent with the study of Roh et al. (2023), who argue that the threat related to the perception of users with robo-advisors put concern on system failure, algorithm errors and data security, which are linked with a decrease in intention to adopt robo-advisors. Another probable reason for this inverse relation is the lack of human oversight in the advisory process. Investors feel reluctant to entirely embrace the automated systems being afraid of the absence of human intervention in the decision making. This lack of human participation negatively impacts the intention to use robo-advisors. Some investors also consider algorithms complex as they are perceived as a threat to the users, particularly those having a lack of financial literacy. In this way, the security as well as privacy of data pose a threat to the safety of sensitive information processed and stored by robo-advisors. Threats to data security tend to reduce trust in robo-advisors. In addition to it, the AI-driven insights stem perceived threats from a lack of industry standards and regulatory oversight to influence the trust of retail investors in the robo-advisors by raising questions on the accountability and reliability of this platform. The researchers (Hwang et al., 2021) also find that in the period of financial crunch, investors are reluctant to trust the robo-advisors, leading to a negative relation with their intention to use.

CONCLUSION AND POLICY IMPLICATION

The German market experts assess the value of assets that robo-advisors are increasingly managing. The policy implications of this research study are for service providers related to robo-advisory, retail investors, advisory firms related to traditional finance, managers, and policymakers.

Implications for Theory

Customers have complex wants and needs, and human judgment is required for solving complex problems, specifically those related to human feelings and emotions since they cannot be entirely ignored. The interface of humans is often supportive for clarifying solutions of wealth, giving assurance, and explaining complex situations to make sure that customers have clarity about the product suitability and product recommendation. Among different advisory modes: human, robot and hybrid, hybrid solutions have the best alignment with the demand for satisfaction of all kinds of investors and for driving the economy towards growth. The advice on investment given by robo-advisors will be more sophisticated and precise; particularly by making improvements in the questionnaires and by making integration of a large part of financial instruments. However, human advice will always be greeted by particular investors who are looking for profound understanding. The choice of more than one option may facilitate companies and advisors to set apart this service supply and reach a wide panorama of customers. Retail investors should examine the companies and their backgrounds before using their services.

Implications for Practice

The outcomes of this study are important for service providers related to robo-advisory in considering the imperative factors motivating the adoption of robo-advisory in Germany. The evaluations and ratings of service providers can encourage prevailing users of robo-advisory to share and promote their experiences by means of evaluations and rankings on social media. This social media information can encourage new and potential users to adopt the services of robo-advisors. In order to build trust in the consumers of robo-advisors, the industry regulators of robo-advisors should take steps related to advertisements and awareness campaigns in order to emphasize compliance with tools protecting the privacy of the data of consumers by the service providers. Moreover, trust can be increased in robo-advisory service providers if they profile risk based on customized services. The personalized and customized services to consumers having different tolerance of risk, different personality traits, and different biases with changing personal and business aims can offer opportunities to service providers related to robo-advisors. They can play the crucial role of interfacing between the customers, their needs, and the right use of technology. As a result, the growing level of trust can enhance the adoption of digitalized financial advisors in Germany.

Furthermore, the service industry of robo-advisory can increase the awareness and financial knowledge of potential consumers about the automated financial robo-advisors. In this field, online education can be specifically effective in this era. Therefore, the service providers of robo-advisors should deliver their prospective customers with adequate information pertaining to the digitalization and technological aspects of their products by means of proper education. Proper education and correction of misinformation pertaining to service and technology behind the service can also be helpful in reducing the level of perceived risk and to focusing on the benefits of the service. Therefore, education can become an additional factor in raising customers' intention to implement robo-advisors. Additionally, the providers of robo-advisory can concentrate on the wants of investors by focusing on the pros of robo-advisors pertaining to unbiasedness, cost, and transparency in comparison to traditional human advisors. After concentrating on these factors, the service providers can enhance their customer base and get a large share of the market. The current needs and behaviour of potential markets should be targeted by the robo-advisors according to their needs. Companies, that offer portfolio management and digital financial advice, want to think about expanding their business models to better serve investors who are more risk averse. For example, robo-advisors may also want to provide advice on real estate financing and insurance products, as these are seen by retail investors as less risky.

The findings of this study are also supportive for advisory firms related to traditional finance as these are the firms affected after the introduction of robo-advisory financial services in the financial market. Therefore, traditional advisory firms are needed to keep offering the services of robo-advice. With the rise in the technological era, traditional advisory firms should consider shifting towards online automated platforms for financial advisory to sustain survivability and relevance. Traditional finance advisory firms should respond to new and improved products and services at competitive rates.

The results of this research have implications for regulators too. The regulators can start education programs to spread awareness of the services related to robo-advisory, increasing the confidence level and knowledge of consumers. Currently, there is a gap between the prevailing methodology of robo-advisors and the current methodological developments, along with the expectations of retail investors. Therefore, policymakers are required to conduct fundamental changes in the robo-advisory sector. The individualized, sophisticated, and novel methods are required to be introduced widely like vehicles which can not only improve performance but also be used as marketing tools for attracting new investors. This step can raise methodological competition among the participants of the market; thereby improving the services of robo-advisory and leading it towards maturity. In this way, the market of robo-advisory will become saturated with diverse companies and diverse offers.

Future Research Directions

The results of this research study provide future directions for researchers. They should know the risk attitude of retail investors is not considered in the financial field, but the personal characteristics (for instance, life orientation, statistical expertise, and locus of control) should impact the investment decision of asset class and service provider. These characteristics should become part of future studies. Although new, specifically pure digital providers of financial services have arisen recently, the research studies should emphasize the features impacting the long-run relation between the service provider and retail investor, including the probability of changing them. Moreover, the researchers are required to access the impact of individual traits on the money an investor is keen to invest using a robo-advisor and on various portfolio other than a mere stock and bond mix. Examining the hidden variables that influence investors when they make investing decisions may prove to be a fruitful avenue. Additional research ought to concentrate on additional robo-advisors as well as other user categories.

Limitations of the Study

However, this study has some limitations as well, which are listed as follows:

- The target population of this study is retail investors and confined to one country i.e. Germany.
- The purposive sampling technique is used for this study, which is a non-probability sampling technique and data is gathered from LinkedIn, and Facebook
- Data is collected through a questionnaire and at one point in time therefore it is a cross-sectional study. The survey was launched on January 1, 2024, and remained open for responses until January 20, 2024
- Data is collected of dependent and independent variables through one instrument.

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