Review

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A Scoping Review on the Factors Affecting the Adoption of Robo-advisors for Financial Decision-Making

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Abstract

Robo-advisors have recently gained popularity as an algorithm-based method of simplifying financial management. The present study explores the factors that lead many potential consumers to use Robo-advisors in financial decisions. Adopting a scoping review approach formulated by Arksey and O'Malley, the study examines the factors affecting the acceptance and usage of financial Robo-advisors in different parts of the world. The results suggest that performance expectancy, effort expectancy, trust in technology, financial knowledge, investing experience, cost-effectiveness, facilitating conditions, and intrinsic motivation are positively related to adopting Robo-advisors. On the contrary, anxiety, risk perception, investor age, data security, and behavioral biases negatively influence the investor attitude toward Robo-advisors. This creates a barrier to the diffusion of financial Robo-advisors among the investors. The study concludes by providing recommendations to service providers, policymakers, and marketers for the speedy distribution and acceptance of algorithms for the public's financial decision-making. The study identifies gaps in the existing literature and suggests areas for future research for aspiring academics.

Keywords

Artificial Intelligence, Financial Advice, Fintech, Robo-advisors, Scoping Review, Technology Adoption

JEL Classification

D14, G11, G23, O14, O33

Introduction

Personal investment management is not everyone's cup of tea. Saving for the future and productive investment management remain tedious for many (Tam & Dholakia, 2014). However, investment management is crucial in achieving investment goals and fulfilling long-term investment dreams. The right advice can help select an optimal investment portfolio and achieve the maximum possible returns (Crager et al., 2016). Consequently, people rely on advice from various sources to choose the best investment to satisfy their investment objectives. Financially literate individuals gather information, analyze potential gains and losses, and make financial decisions (Westermann et al., 2020). Meanwhile, for financially illiterate people, it becomes challenging to make calculated decisions in their capacity. They may rely on family, friends, and peers to resolve asset allocation issues (Zhang et al., 2021). However, the return on investment for such advice is not always assured. That is precisely where banks and financial institutions play a part in providing their valuable advisory services (Abdulquadri et al., 2021).

The financial advisory sector has evolved multifold in the last few decades. With the rapid advancement of technology, there is a shift from the typical "brick and mortar" model of financial advisory to algorithm-based personalized investment advisory (Kshetri, 2021). Initially, the consultants and clients used to have one-on-one physical meetings to discuss potential investment options. After the invention of telephones, consultancy firms introduced telephonic advisory services, eliminating the client’s need to meet the advisor physically (Reiter-Gavish et al., 2021). Smartphones and the internet further facilitated the advisory industry with mobile applications and online client-consultant interaction. Financial technologies, popularly known as FinTech, provide extraordinary possibilities to recreate and modify the present financial service industry (Mamoshina et al., 2018). The idea of FinTech goes beyond consumer digitalization and internet banking (Alt et al., 2018). It incorporates the speedy development and thriving introduction of innovative, disruptive, and unique technology-based instruments to meet users' financial needs and demands (Chen et al., 2019; Hua et al., 2019). As technology continues to advance, the

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interest of banks and insurance companies in digital financial advisory, widely known as Robo-advisory, is on the rise (Jung, Dorner, Glaser, et al., 2018).

Robo-advisory services offer investment advice without any human interaction. They represent a novel, exciting, and creative development in the digital asset management sector. The automated investment advisory process ranges from accumulating investors' information, establishing financial goals, designing investors' risk profiles, and finally managing and adjusting the investors' portfolios (Faloon & Scherer, 2017; Gomber et al., 2017; Tertilt & Scholz, 2018). Robo-advisors provide 24/7 access to low-cost financial advisory services and are convenient (Park et al., 2016; Uhl & Rohner, 2021). As a result, finance companies and banks are coming up with Robo-advisors to get a competitive advantage (Puhle, 2019). Indeed, as of 2020, Robo-advisors managed assets worth more than US$ 1 trillion worldwide. The value of assets under management is estimated to increase and reach nearly US$ 2.9 trillion by 2025 (Statista, 2021). Hence, an extensive prospective market line exists in Robo-advisory. In addition to banks and financial institutions, various tech-based businesses seek investment opportunities in the sector (Ozili, 2021). However, the acceptance of Robo-advisory by investors for investment decision-making has been modest thus far (Jung, Dorner, Weinhardt, et al., 2018). Even while people of all socioeconomic and demographic backgrounds are becoming more interested in Robo-advisors, there is a shortage of effective promotion of such services (Phoon & Koh, 2018). Furthermore, most studies on Robo-advisors focus on legal and technical issues (Glaser et al., 2019; Ji, 2017). Therefore, greater emphasis on customer views and numerous behavioral factors impacting disruptive and innovative technology adoption, such as Robo-Advisors, is required.

Using Arksey and O'Malley's (2005) model, the researchers review published studies on the adoption and the factors influencing the adoption and use of Robo-advisors. Arksey & O'Malley, (2005) propose a framework widely used for scoping reviews. Further, the study describes the practical and theoretical implications of chosen studies and aims to give suggestions to service providers and policymakers. Moreover, the study also identifies gaps in the existing literature and suggests areas for future research for academicians. The remainder of the paper is structured as follows. The authors provide a detailed, step-by-step article selection process for the scoping review in the research methodology section. The authors summarize the existing literature under various themes in the results section and present a framework for further research. The discussion section highlights the study's findings and provides suggestions to policymakers and service providers. The conclusion section offers a brief closure to the study. The last section of the paper discusses the scope for further research.

Research Methodology

The paper adopts a scoping study approach formulated by Arksey and O'Malley (2005) to review the existing literature. Arksey and O'Malley's (2005) approach is versatile and adaptive. Unlike Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), which is very rigid, one can modify the strategy to match one's study topic, goals, and resource limitations. The framework may be tailored and changed as needed, making it appropriate for various study scenarios. Moreover, when opposed to doing a systematic review, Arksey and O'Malley's (2005) method for scoping reviews is more time-effective. This method enables researchers to comprehensively overview the research environment within a set timeline and budget. There are five significant steps in the scoping review framework: identification of the research question, identification of relevant studies, selection of studies for review, charting the data, and summarization of results (Arksey & O'Malley, 2005). There is one more optional consultation step whereby the industry experts provide insights on the study topic beyond the existing literature. This study adopts all six stages of the Arksey and O'Malley (2005) framework (see Fig. 1).

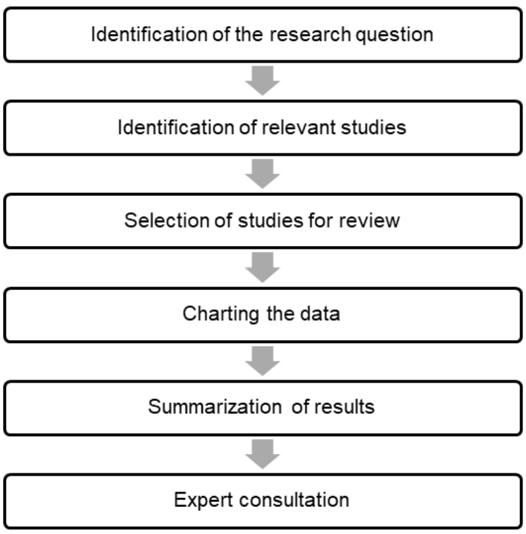

Fig. 1. Steps in the Arksey and O'Malley (2005) framework for scoping review.

The first stage is the identification of the research question. The present study attempts to answer the research question – What factors affect the acceptance and usage of financial Robo-advisors across different parts of the world? Moreover, the research question must be developed considering the specific idea, study population, and outcomes (Levac et al., 2010). The target population for the study is potential and existing users of Robo-advisory services for investment decision-making. Furthermore, the target sample is global and focuses only on adults (as possession of investable assets is a prerequisite to taking investment advice).

The second stage is the identification of relevant articles for the review. The study systematically searched scholarly articles from various academic databases like Emerald Insight, JSTOR, ProQuest, Google Scholar, and Taylor and Francis using multiple search terms like "Robo-advisors AND Adoption," "Robo-advisors AND Acceptance," "Robo-advisors AND Usage," "Robo-advisors AND Awareness," "Robo-advisors AND Consumer Perception," "Robo-advisors AND Intention to use," "Fintech AND Adoption," "Fintech AND Acceptance," "Fintech AND Usage," "Fintech AND Intention to Use." The primary search identified 836 articles covering a wide range of topics. Table 1 depicts the number of articles appearing per the search terms used in various databases.

Table 1. Initial articles search from various databases.

Database	No. of Articles
Emerald Insight	190
JSTOR	97
ProQuest	102
Google Scholar	359
Taylor and Francis	88
Total	836
Search Terms	**No. of Articles**
Robo-advisors AND Adoption	102
Robo-advisors AND Acceptance	71
Robo-advisors AND Usage	63
Robo-advisors AND Awareness	31
Robo-advisors AND Consumer Perception	53
Robo-advisors AND Intention to use	47
Fintech AND Adoption	214
Fintech AND Acceptance	91
Fintech AND Usage	109
Fintech AND Intention to Use	55
Total	836

Note: The number of articles displayed in Table 1 is as of June 17, 2022

The third stage is the selection of studies for review, as depicted in Fig. 2. Following the initial screening, 274 articles that appeared in several databases were deleted, leaving 562 for additional filtering. The articles then went through a journal quality and citation check, where 211 articles from low-quality journals were excluded from further review. Low-quality journals are characterized by a lack of peer review, predatory practices, poor editorial practices, lack of indexing, and Low Cite Score or impact factor. Research work published in such journals lacks credibility and academic rigor. The researchers then looked into the article's abstract to ensure coherence with the present study and selected 183 writings for further investigation. The review continued by reading the papers, considering papers published in peer-reviewed journals, and excluding articles not primarily focusing on automation in the investment advisory sector.

Further, the exclusion criteria considered studies that were not original research, were published in languages apart from English, were published before 2015, and did not primarily focus on adopting financial Robo-advisors. Finally, the researchers selected 39 articles that satisfied the inclusion-exclusion criteria. The selected articles were thoroughly read and analyzed.

In the fourth step, the researchers developed a review matrix using Microsoft Excel software to record the relevant data from selected publications. Following a comprehensive analysis of the papers, the study's title, author(s) information, publication year, and study location(s) were recorded, along with other pertinent data such as the study's purpose, methodology, variables examined, notable findings, and implications. The researchers added another column to show the breadth of future research to identify research questions for future studies. The data charting assists in synthesizing the findings of selected studies and reporting the study results.

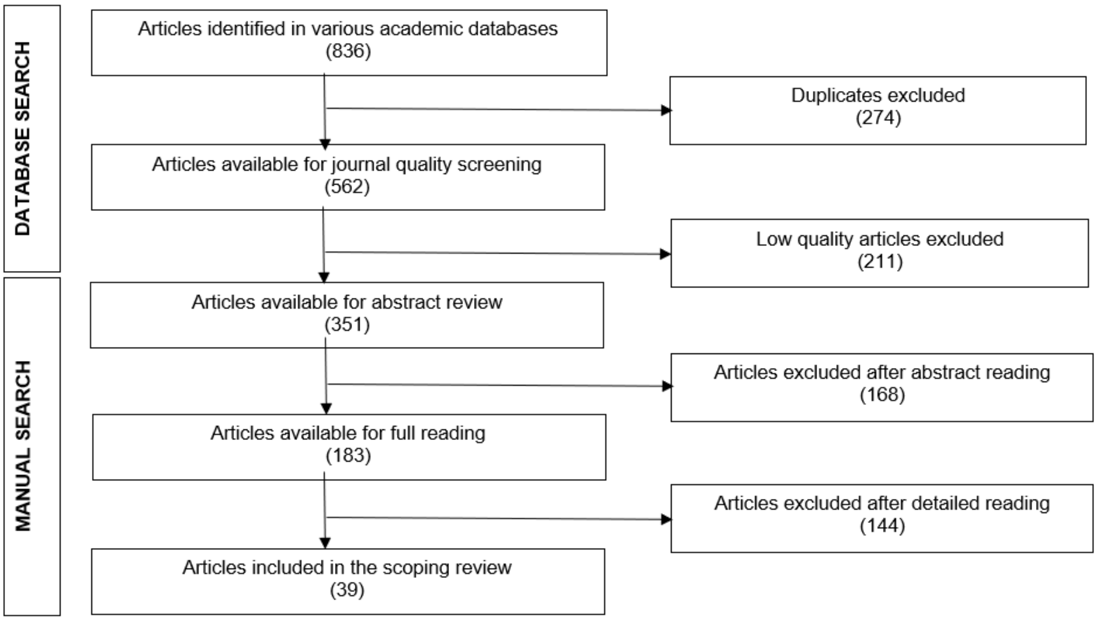

Fig. 2. Overview of the process of choosing articles for the review.

The results are collated, summarized, and reported in the fifth stage. This stage includes reporting on the publication trends, methodology, theoretical background, general overview and constructs tested in the reviewed articles. The results section of the study contains a detailed data summary and discussion.

Lastly, after the compilation of study results, the authors consulted two industry experts to validate and comment on the results. The experts work in a company’s top and middle management, providing Robo-advisory services in India. The authors refrain from disclosing the respondent's name to maintain the confidentiality of personal data. The consultation process took place over telephone voice calls and Google Meet. The discussion commenced with a quick introduction of the researchers. Further, the authors explained the study's purpose and the respondent's role in this study. The exhaustive consultation process commenced after the consent of the experts. The consultation process lasted for an average of 24 minutes.

Results

While traditionally not so prevailing, scoping reviews are gaining popularity in social science (Munn et al., 2018). The researchers read and analyzed the 39 selected papers to arrive at the final results. The following sub-sections depict the publication trends, theories adopted, methodology, and general overview of the selected articles. Further, after thoroughly reading the chosen papers, the researchers identified the themes for the study.

Publication Trends

The researchers organize the papers based on the year of publication. Fig. 3. illustrates the spread of publication dates of the articles, ranging from 2015 to 2022. As the present study attempts to capture the factors leading to the acceptance of financial Robo-advisors in the present scenario, articles published before 2015 were excluded from the current study. Results suggest that the adoption domain of Robo-advisors has gained increasing momentum, with 12 new publications in 2021. The article screening went up to June 17, 2022. Seven publications were recorded in the year's first half, confirming an upward trend in the domain.

To understand the regional concentration of the studies, the authors recorded the regions covered by the reviewed studies. A few studies collected data from more than one country to expand their scope. Table 2. details the distribution of the articles based on the area covered in the research. The results indicate that most studies utilize data collected from America (n=11), wherein a majority of the studies (n=10) focus on the United States, and only a few gathered data from the rest of North America (n=2). Looking at the Asian continent, studies (n=13) were conducted in China, India, Taiwan, Korea, Indonesia, and Malaysia. These were followed by studies focusing on European data (n=8), including data collected from Britain, Portugal, Germany, Poland, and Sweden. Further, some studies (n=2) looked at the worldwide perspective of Robo-advisory. Lastly, several studies (n=7) refrained from reporting the country of analysis, quoting the conceptual nature.

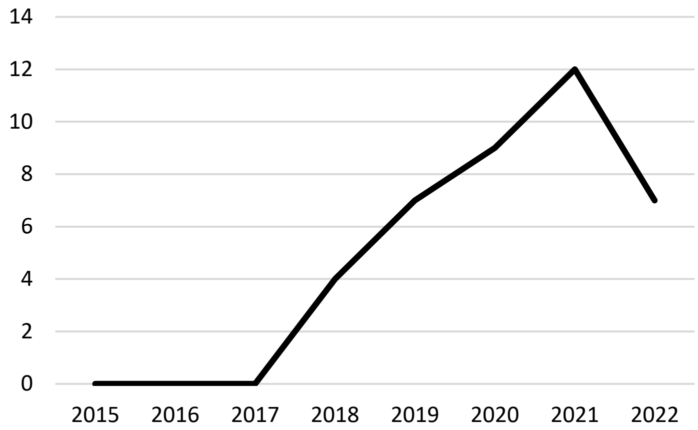

Fig. 3. Number of papers published during the time frame of the scoping review.
Note: The number of articles displayed in 2022 is as of June 17, 2022

It is not astonishing to note that many studies focused on developed economies, especially the USA, Germany, the UK, Poland, and Taiwan, as they are at the vanguard of investment and technology. The fintech segment in the USA has seen a considerable increase since 2017. The assets' value increased three times to reach US$ 1 trillion by 2021 and is further estimated to grow and reach over US$ 1.94 trillion by 2025 (Statista, 2021). Conversely, developing nations reported a handful of studies due to the infancy stage of Artificial Intelligence (AI) driven services.

Table 2. Country of analysis.

Country	Number	Reference
America		
United States	10	(Brenner & Meyll, 2020; Chhatwani, 2022; Fan & Chatterjee, 2020; Hohenberger et al., 2019; Northey et al., 2022; Rossi & Utkus, 2020; Shanmuganathan, 2020; Tokic, 2018; Wang & Pradhan, 2020; Zhang et al., 2021)
North America	2	(Belanche et al., 2019*; Flavián et al., 2022)
Europe		
Britain	1	(Belanche et al., 2019*)
Portugal	1	(Belanche et al., 2019*)
Germany	4	(Atwal & Bryson, 2021; Au et al., 2021; Bruckes et al., 2019; Puhle, 2019)
Poland	1	(Warchlewska & Waliszewski, 2020)
Sweden	1	(Nourallah et al., 2022*)
Asia		
China	2	(X. Cheng et al., 2019; Huang et al., 2022)
Taiwan	2	(Y. M. Cheng, 2021; Yeh et al., 2022)
India	5	(Bhatia, Chandani, Atiq, et al., 2021; Bhatia, Chandani, Divekar, et al., 2021; Bhatia et al., 2020; D'Acunto et al., 2019; Menon & Ramakrishnan, 2021)
Korea	1	(Sa et al., 2018)
Indonesia	1	(Sani & Koesrindartoto, 2019)
Malaysia	2	(Gan et al., 2021; Nourallah et al., 2022*)
Worldwide	2	(Phoon & Koh, 2018; Tsai & Chen, 2022)
Country not reported	7	(Agarwal & Chua, 2020; Hentzen et al., 2021; Hildebrand & Bergner, 2021; Niszczota & Kaszás, 2020; Uhl & Rohner, 2021; Wexler & Oberlander, 2020, 2022)

Note: * indicates data collected from multiple countries

Theories Adopted

Hunt (2018) emphasizes the significance of theoretical background and theory development in academic research. He states that theories lead to the evolution of disciplines and encourage future researchers to expand the existing literature. Researchers consider theories as guiding forces to increase the scientific understanding of various social phenomena (Hunt, 2010). The authors analyzed the theories adopted by the selected articles to understand the principal theoretical underpinning better. Table 3. displays the list of theories applied or referred to by the authors. The results suggest that the notable theories utilized by researchers to explain Robo-advisor adoption are the Unified Theory on Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003, 2012), the Technology Acceptance Model (TAM) (Davis, 1989), the Diffusion of Innovation Theory (DOI) (Rogers, 1995). While most studies use single theories, only two (Menon & Ramakrishnan, 2021; Sa et al., 2018) utilize multiple theories to conclude. Remarkably, more than half (n=22) of the articles included in the scoping review did not specifically refer to or apply any distinct theory. This is due to the conceptual nature of the articles.

Table 3. Theories adopted by the articles selected for scoping review.

Theory	Number	Reference
Expected Utility Theory	1	(Bhatia, Chandani, Divekar, et al., 2021)
Trust Transfer Theory	1	(X. Cheng et al., 2019)
Diffusion of Innovation	2	(Fan & Chatterjee, 2020; Tsai & Chen, 2022)
Technology Acceptance Model	4	(Belanche et al., 2019; Menon & Ramakrishnan, 2021; Sa et al., 2018; Sani & Koesrindartoto, 2019)
Self-Service Technology Adoption	1	(Zhang et al., 2021)
Unified Theory on Acceptance and Use of Technology	4	(Atwal & Bryson, 2021; Gan et al., 2021; Sa et al., 2018; Yeh et al., 2022)
Theory of Planned Behaviour	1	(Menon & Ramakrishnan, 2021)
Technology Readiness Index	1	(Flavián et al., 2022)
Exception Configuration Model	1	(Y. M. Cheng, 2021)
Efficient Market Hypothesis	1	(Tokic, 2018)
Agency Theory	1	(Chhatwani, 2022)
Theory of Perceived Risk	1	(Nourallah et al., 2022)
No Theory Reported	22	(Agarwal & Chua, 2020; D'Acunto et al., 2019; Hildebrand & Bergner, 2021; Niszczota & Kaszás, 2020; Wexler & Oberlander, 2022) and 17 more

The results further demonstrate a mix of both theory-driven and data-driven research. Theory-driven research is prominent in social sciences, and it includes scientific inquiry, ranging from hypothesis development, collecting data, data analysis, and, eventually, testing the hypothesis (Maass et al., 2018). Whereas information system sciences usually tend to adopt data-driven research. Technology adoption theories, such as the TAM and the UTAUT, with some additional constructs, attempt to identify the causal factors of customers' intention to utilize Robo-advisors for financial decision-making (Atwal & Bryson, 2021; Xu et al., 2020).

Methodology

The researchers further analyzed the research designs adopted by the reviewed studies. Table 4. summarizes the research design into four categories: qualitative, quantitative, conceptual, and mixed methods. Of the 39 studies reviewed, 62% adopted a quantitative approach, 31% were qualitative in nature, 5% were conceptual papers, and 2% applied mixed methods. Among the qualitative studies, the research approach is highly skewed toward surveys (n=16) as compared to experimental studies (n=3) and secondary data analysis (n=5). This could be possible because adoption studies intend to develop a framework from the first-hand information collected from the study participants. Twelve studies adopted a qualitative approach toward Robo-advisory, including case studies (n=4), interviews (n=3), review papers (n=2), focused group discussions (n=1), a systematic review (n=1), and document analysis (n=1). The results indicate an increasing interest in qualitative research as it grants the ability to understand and interpret individuals' perceptions meticulously. Lastly, Cheng et al. (2019) applied mixed methods, a thriving research methodology deriving the benefits of semi-structured interviews followed by an online survey.

Concerning the data collection, most studies (n=20) utilized first-hand information from Robo-advisors' beneficiaries, such as investors and potential investors. Fig. 4. displays the various sources of data explored by the reviewed articles. Several studies (n=6) include data from private and public databases, including Bloomberg, National Financial Capability Study (NFCS), and Standard & Poor's (S&P). Such datasets enable researchers to extract extensive data and increase the sample observations. As a consequence, the results of the studies can be better generalized.

Table 4. Summary of the research design of reviewed articles.

Research Design	Count	References
Quantitative		
Survey	16	(Au et al., 2021; Belanche et al., 2019; Bruckes et al., 2019; Flavián et al., 2022; Hildebrand & Bergner, 2021; Sa et al., 2018) And 10 more
Experiment Study	3	(Niszczota & Kaszás, 2020; Northey et al., 2022; Zhang et al., 2021)
Secondary Data Analysis	5	(Brenner & Meyll, 2020; Chhatwani, 2022; D'Acunto et al., 2019; Fan & Chatterjee, 2020; Puhle, 2019)
Qualitative		
Case Study	4	(Phoon & Koh, 2018; Rossi & Utkus, 2020; Shanmuganathan, 2020; Tokic, 2018)
Interviews	3	(Atwal & Bryson, 2021; Bhatia et al., 2020; Tsai & Chen, 2022)
Review Paper	2	(Agarwal & Chua, 2020; Huang et al., 2022)
Systematic Review	1	(Hentzen et al., 2022)
Document Analysis	1	(Uhl & Rohner, 2021)
Focused Group Discussion	1	(Bhatia, Chandani, Atiq, et al., 2021)
Conceptual Paper	2	(Wexler & Oberlander, 2020, 2022)
Mixed Methods	1	(X. Cheng et al., 2019)

Bhatia, Chandani, Atiq, et al. (2021) conducted interviews and focus group discussions with industry experts and managers in fintech companies. Case studies majorly utilize data from company records (n=4) and provide an in-depth analysis of the performance and utilization of Robo-advisors (Phoon & Koh, 2018; Rossi & Utkus, 2020; Shanmuganathan, 2020; Tokic, 2018). Apart from this, a few studies refrained from specifying the source of data collection (Agarwal & Chua, 2020; Wexler & Oberlander, 2020).

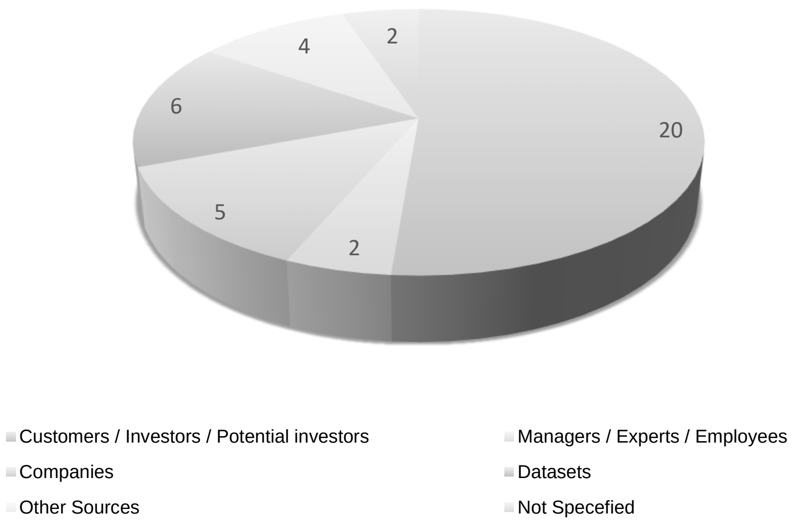

Fig. 4. Source of data collection.

General Overview

Robo-advisory uses automated technology, often driven by algorithms and AI, to offer financial guidance and manage client investments (Agarwal & Chua, 2020). The extent of automation can vary, and studies may look into various areas of robo-advice. Depending on the automation level, studies have classified robo-advice platforms ranging from entirely automated platforms that give advice and execute transactions without human interaction (Au et al., 2021) to hybrid models that incorporate automated guidance with some human engagement or oversight (Wexler & Oberlander, 2020). Further, the reviewed studies investigate the different kinds of financial services Robo-advisors offer. These services may include portfolio management (Niszczota & Kaszás, 2020), asset allocation (Uhl & Rohner, 2021), retirement planning (Chhatwani, 2022), tax optimization (Phoon & Koh, 2018), and others.

Disruptive advancements in technology are transforming the finance sector drastically. Following the internet and smartphones, algorithms are paving their way into financial services. Financial advisory is also welcoming the use of AI to assist their clients. However, this transition has not been smooth for service providers as some customers are skeptical about using algorithms in their financial decision-making. After thoroughly reading the selected research articles, the authors identified common factors in multiple studies that impacted the acceptance and adoption of Robo-advisors in financial decision-making and framed the following themes.

Perceived Usefulness

People switch to new technology, seeking better performance and reduced efforts. Perceived usefulness is how people believe using a Robo-advisor would enhance their investment returns (Davis, 1989). Hence, a system or product high in perceived usefulness is the one people believe would lead to a positive use-performance relationship. Potential users' perceived effectiveness of Robo-advisor significantly and positively impacts the behavioral intention to use these innovative services (Atwal & Bryson, 2021; Sa et al., 2018). A study by Sani and Koesrindartoto, (2019) found that the perceived usefulness of Robo-advisors increases people's intention to use them directly by 48.5 percent. Furthermore, the Indian participants believe that the perceived effectiveness of Robo-advisory services substantially impacts their attitude towards behavioral intention to use Robo-advisors in wealth management (Menon & Ramakrishnan, 2021). However, Belanche et al. (2019) concluded that even though the perceived usefulness positively affects the investors' attitude toward Robo-advisors, there is no significant evidence of the relationship between the perceived use and intention to adopt financial Robo-advisory services among the American masses.

Perceived ease of use

Technologies that are simple to understand and easier to use have a higher diffusion rate compared to complex technological innovations. Perceived ease of use is how people believe using a specific product or system would be easy and effort-free (Davis, 1989). Thus, a system or product high in perceived ease of use is the one for which people believe it would provide freedom from difficulty in operating the device and be more user-friendly. Individuals' perceived ease of use of Robo-advisor positively influences the perceived usefulness and attitude toward using such novel Robot-based financial advisory services (Belanche et al., 2019). Further, the positive attitude toward using Robo-advisors creates a desire to use them and eventually influences the behavioral intention to use Robo-advisory (Sani & Koesrindartoto, 2019). Adding to the evidence, a study organized in South Korea concluded that with all other variables kept constant, a Robo-advisory service perceived as more straightforward to use than other financial advisory services is more likely to be accepted by users (Sa et al., 2018). Among the various personal characteristics of individuals, the convenience of using Robo-advisory services, the self-efficacy of an individual, and the social influence are solid guiding factors of the behavioral intention towards using Robo-advisory in wealth management (Menon & Ramakrishnan, 2021).

Trust

Trust is the foundation stone of every relationship. In technology application, trust refers to the readiness to be vulnerable based on the positive supposition towards a novel technology (McKnight et al., 2002). Trust is crucial to accepting and adopting self-service technologies and AI in the service sector (Ostrom et al., 2019). On a similar line, an individual's trust in Robo-advisory services directly relates to adopting financial Robo-advisors (Nourallah et al., 2022). Several researchers found the relationship between trust in Robo-advisors and intention to adopt them statistically significant in different parts of the world (Gan et al., 2021; Sani & Koesrindartoto, 2019; Wang & Pradhan, 2020). Bruckes et al. (2019) found that trust in banks positively relates to trust in financial Robo-advisors. This initial trust in Robo-advisors helps the service providers predict the use intention of customers. The initial trust in AI-based Robo-advisors develops by creating structural assurances and safeguarding security, privacy, and reliability. Service providers can provide more open information, including examples of how risk profiles are created and descriptions of the asset allocation process, to build early confidence among the investors.

While comparing the individuals' perceptions of humans and Robo-advisors in the context of financial services in the USA, trust emerged as a vital deciding factor for adoption (Zhang et al., 2021). Additionally, Zhang emphasized that Robo-advisors do not induce the same level of trust as human advisors. This increased confidence in human experts emerges primarily from emotional trust, which involves a person's intuition or faith as well as their emotional response to the investors' needs. As the Indian stock market is emotion-driven, the financial Robo-advisors lack trust in performance in times of distress and during challenging market conditions (Bhatia, Chandani, Atiq, et al., 2021). Hildebrand & Bergner, (2021) suggests that fintech companies must work on building conversational Robo-advisors as investors attribute a considerable level of trust towards dynamic, turn-taking, and dialogue-based machines. An interactive user interface with social cues provides a sense of connectivity with the Robot, enhancing the overall confidence in the portfolio they recommended. Into the bargain, affirmative government regulations and precise supervisory control are a must in gaining investors' trust in algorithm-based advisory services (X. Cheng et al., 2019).

Risk

Utilizing any new technology, especially in the digital context, is linked with an inherent risk. The risk is paramount to the unpredictability of the outcomes of innovative digital techniques and the fear of loss of privacy and money in the configuration process (Malaquias & Hwang, 2016). Investors with higher investment risk tolerance are more likely to adopt Robo-advisors in wealth management (Fan & Chatterjee, 2020). Customers' impression of insecurity with the technology had a significant negative impact on their intentions to use financial Robo-advisory services (Flavián et al., 2022). Conversely, Bruckes et al. (2019) found that although the perceived risk of Robo-advisors harms customers' trust in Robo-advisors, the risk factor does not affect the behavioral intention to use financial Robo-advisory services. Older adults in the U.S. reported that they do not consider the level of risk aversion as a deciding factor for the adoption of financial Robo-advisors and are open to using new technology in investment (Wang & Pradhan, 2020).

Similarly, another study by Au et al. (2021) states that there is no relation between investors' risk appetite and the likelihood of adopting a Robo-advisor offering sustainable portfolios. Moreover, compared to human financial advisors, investors believe that Robo-advisors can accurately judge and determine the investor's risk appetite by reducing investor biases while conducting risk analysis and investor profiling. A case study conducted in the U. S. shows that Robo-advisors improve investors' comprehensive risk-adjusted performance by reducing investors' investments in the money market mutual funds and increasing their holdings in the bond market (Rossi & Utkus, 2020). Further, to make Robo-advisors more effective, much work has to be done to build mindful and personalized questionnaires to precisely evaluate the risk-taking magnitude of investors (Bhatia et al., 2020).

Prior knowledge and familiarity

People are different from one another in terms of knowledge and skills. Individuals' differences in their prior knowledge and familiarity with robots also play a crucial role in adopting Robo-advisors (Castañeda et al., 2007). Similarly, those with fundamental investment understanding and subjective financial expertise are positively correlated with the likelihood of utilizing financial Robo-advisors (Fan & Chatterjee, 2020). Moreover, experienced investment clients exhibit a positive attitude toward using technology and proactively adopt sustainable Robo-advisors (Au et al., 2021). Users with a low understanding of AI tend to be influenced faster by others' opinions about Robo-advisory services (Belanche et al., 2019). Hohenberger et al. (2019) conducted a study in the USA, revealing that individuals with extensive financial experience demonstrate lower anxiety levels while using AI-powered Robo-advice. Further, they exhibited high levels of joy concerning the idea of using a financial Robo-advisor.

Post-adoption of Robo-advisors, investors with little prior investment experience and high cash holdings benefited more from advice than investors with high investment knowledge and enormous cash holdings (Rossi & Utkus, 2020). Familiarity with robotics and AI systems moderates the relationship between the antecedents (performance expectancy, effort expectancy, facilitating conditions) and the behavioral intention to use Robo-advisory (Yeh et al., 2022). Gan et al. (2021) further revealed that investors with higher perceived financial knowledge in Malaysia exhibited a stronger desire to adopt Robo-advisors for financial advice.

Behavioral bias

Traditional advisors, say bank clerks, usually adopt a one-size-fits-all approach to suggest investment portfolios and knowingly or unknowingly transfer their behavioral biases to the clients. Robo-advisors' inherently passive, economical, and disciplined guidance helps customers avoid behavioral biases and expensive asset management, leading to better net investment performance (Uhl & Rohner, 2021). Robo-advisors are based on AI-facilitated algorithms and provide investors with impartial investment advisory services. An investment broker or professional fund manager making investment decisions on behalf of their client may be biased (Kumar & Goyal, 2015) based on the market situations; however, a Robo-advisor will not (Bhatia, Chandani, Divekar, et al., 2021). Investors adopting Robo-advisors for financial decision-making experience diversification benefits and noticeably reduced behavioral biases, majorly in trend-chasing, disposition, and rank effects (D'Acunto et al., 2019). Furthermore, the fact that Robo-Advisors use AI algorithms in investment decision-making and are thus free from biases and human emotions contributes to building trust in this novel technology (Gan et al., 2021). On the contrary, confident investors apprehend that the programmers of Robo-advisor algorithms are also human beings. Therefore, there is a high possibility of passing their personal behavioral biases into programs, eventually not making any difference (Bhatia, Chandani, Divekar, et al., 2021).

Demographic variables

The intention to adopt Robo-advisors for financial decision-making varies based on the specific demographic characteristics of investors (Guo, 2020). The investors perceived as early adopters of Robo-advisors are unlikely to be more than 65 years of age but are more likely to own higher investable assets, be more risk-tolerant, and have a good amount of investment knowledge (Fan & Chatterjee, 2020). Investors with more significant investment amounts are less likely to accept the portfolios suggested by AI-enabled systems as there are more dollars in play and higher stakes, making them desire greater control over their investments (Northey et al., 2022). Older adults, specifically those aged 50 years and above, believe that the complexity of technological designs used in Robo-advisors is not inclusive enough to meet their personal goals and find human financial advisors more convenient than a Robo-advisor (Wang & Pradhan, 2020). Both men and women invest similar amounts in Robo-advisory services and display indistinguishable levels of satisfaction with this investment method, indicating the non-existence of a technological divide between them (Belanche et al., 2019; Warchlewska & Waliszewski, 2020). On the contrary, in an experiment conducted by Niszczota & Kaszás, (2020), it was revealed that female participants strongly dislike Robo-based investment systems as they increase investments in stocks of morally controversial companies whose actions significantly hurt society. Furthermore, educated people demonstrate a positive attitude toward technology and are more likely to adopt Robo-advisors offering portfolios of sustainable companies (Au et al., 2021).

Robo-advisory services in the financial sector represent a prototypical example of algorithms and AI. However, the acceptance and diffusion of disruptive technologies is not an easy task. The review of selected studies suggests that performance expectancy/perceived usefulness, effort expectancy/perceived ease of use, trust in technology, perceived financial knowledge and prior investing experience of investors, social influence, cost-effectiveness, facilitating conditions, and intrinsic motivation are positively related to the intention to use Robo-advisors. Apart from the factors mentioned earlier, numerous other factors eventually impact investors' decisions to espouse Robo-advisors. Reduced investment handling fees (Phoon & Koh, 2018), no minimum investment requirement (Puhle, 2019), quick delivery of advice with a shorter wait time (Agarwal & Chua, 2020), enhanced user interface (Shanmuganathan, 2020), 24/7 accessibility (Wexler & Oberlander, 2020) and reduced physical contact (Huang et al., 2022) are a few among the long. On the contrary, technological anxiety level, risk perception, investor age, data security, and behavioral biases negatively influence the investor attitude towards Robo-advisors, leading to lower diffusion of financial Robo-Advisors among the investors. Fig. 5. illustrates a conceptual framework of the factors affecting robo-advice adoption based on the scoping review.

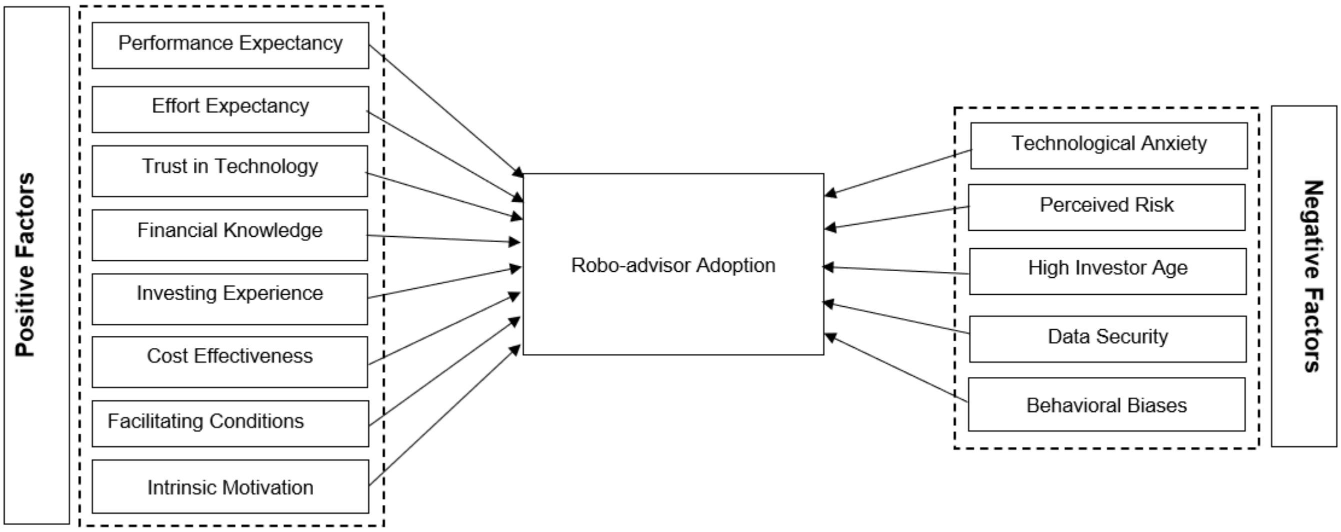

Fig. 5. Conceptual framework of the factors affecting robo-advice adoption.

Both robo-advisors and human financial advisors have certain advantages and disadvantages. The decision between the two is frequently influenced by the preferences, monetary requirements, and complexity of the customers' financial conditions (Zhang et al., 2021). Robo-advisers are becoming increasingly popular due to their affordability and accessibility, yet human financial advisors excel at offering individualized, sympathetic guidance and handling difficult financial situations. One of the most appealing aspects of robo-advisors is their low cost. Since they work through automation and don't require a lot of human interaction, they frequently charge lesser fees than actual financial counsellors (Shanmuganathan, 2020).

On the contrary, some potential customers may be demotivated by the worries about the security of personal information and the dependability of automated systems (Westermann et al., 2020). The fact that Robo-advisors don't have contact with clients on a personal level may be an essential obstacle for some people (Gerrans & Hershey, 2017). Working with a person they can hold responsible for their financial decisions may make clients feel safer. In times of market instability or significant life events, human advisers can connect emotionally and demonstrate empathy better than automated systems. For many customers, having access to a live person to speak with is a crucial motivator (Stolper & Walter, 2017). Further, the lack of transparency and well-defined regulatory framework restrict investors from exploring automated advisory services (Baker & Dellaert, 2018).

Expert Consultation

After completing the review, the authors proceeded to validate the results of the current study with the help of expert consultation. The experts opined that Robo-advisors in the financial industry are a typical example of contactless service. They have the potential to provide a wide range of activities, such as financial planning, asset management, tax planning, retirement planning, client education, and a lot more. Both experts acknowledge the factors identified in the present study as relevant and very much necessary to understand the investors' perceptions towards technology adoption. Though Robo-advisors are still in the infancy stage in India, there is a promising future for such novel services in the coming decade. One of the experts stated that, along with looking at the adoption factors, it is necessary to address the retention of customers:

"Adopting Robo-advisors is one thing, and choosing to use it again and again is another. With marketing and promotion, we can attract new customers every quarter, but what happens after we get them on board is a totally different challenge. It's like when a child goes to a play store, they will pick a vibrant and colourful toy. But it's the utility they derive from the toy that matters. Otherwise, they will go and pick another toy the next time. Similar is the case with new technologies, especially the investment Robo-advisors. People download our apps, make an account with us, and enter into a few tradings. But after that, either they revoke their account or stop making any transactions. So, this is where we need to work further and get the solutions."

The financial landscape is perpetually changing, and it is crucial to remember that adoption factors of automated advisory services differ from one region to another. Adding to the study's findings, several other factors, such as regulatory environment, competing financial services, cultural factors, digital literacy, and internet penetration, significantly decide the future of financial Robo-advisors. When specifically talking about the Indian market, another expert commented:

"A certain degree of digital proficiency and internet connectivity are prerequisites for using robo-advisors. Despite we claim that Internet penetration in India is on the rise, some still have poor digital literacy and limited internet access. It becomes a real challenge to expand the market beyond tire I and tire II cities. Along with all the necessary resources, the regulatory framework significantly influences how Robo-advisory services will thrive in the future, and the regulations governing the Robo-advisory industry in India are somewhat ambiguous. The regulatory authority in India does not distinguish between a Robo-advisor and a human investment advisor posing a huge obstacle in front of us".

Robo-advisors providing financial or investment advice in India must adhere to the Securities and Exchange Board of India (SEBI) - (Investment Advisors) Regulations, 2013. SEBI laws do not distinguish between a human advisor and a Robo-advisor regarding the legally binding and necessary physical agreement between the adviser and the client. When the USP of robo-advisors is to offer inexpensive advisory services without direct interaction between the advisor and the customer, such a directive will make client acquisition more expensive and automated advice services unprofitable. Likewise, policymakers must amend their existing laws to facilitate the diffusion of Robo-advisory services in the financial sector.

Discussion

The present research attempts to develop a framework of technology adoption for financial Robo-advisors. The authors adopt a scoping study approach formulated by Arksey and O'Malley (2005) to review the existing literature and synthesize the factors affecting the adoption of Robo-advice for financial decision-making. The results of the survey provide valuable extensions to TAM and UTAUT models along with the negative aspects. The previous UTAUT only covered the favorable factors affecting technology adoption, disregarding the impact of negative factors that act as a barrier to technology adoption and eventually hamper the adoption of new technologies. The study develops a more comprehensive technology adoption framework (Figure V) that can be tested empirically in the future among various technologies over different domains.

Customer retention is a vital part of any company strategy. While attracting new customers is critical for growth, maintaining existing customers results in enhanced loyalty, higher lifetime value of clients, and good word-of-mouth referrals, all of which contribute to the business's long-term success. As suggested by the experts, there is a lack of studies focusing on enhancing customer retention by Robo-advisor. Hence, academicians may further look into the factors contributing to the increased customer retention in the automated advisory sector and provide valuable insights to the service providers. The expert further added that FinTech and other service providers could improve customer retention rates and establish a loyal client base by prioritizing customer satisfaction and taking initiatives to improve the customer experience. Robo-advisory services for investment decisions are considered incipient in developing economies and have a broad scope in the coming years. However, the majority of the studies reviewed are from the United States of America, the United Kingdom, Portugal, Poland, Germany, Malaysia, and South Korea. It prevents the researchers from extrapolating the findings of publications studied in emerging economies because people's perceptions vary depending on their culture, standard of living, and economic situation. Future research needs to consider obtaining a more comprehensive sample, especially from developing countries, because with rapid digitalization, there is a bright future for Robo-advisory services in developing economies.

Further, the amount of personalization, effectiveness, and convenience customers demand from the services they use is expected to increase as they become more aware of AI's possibilities. FinTech providers must adjust to these growing demands by using AI-driven features and solutions to sustain in the competitive market. Marketers and service developers should divide the market into various segments to facilitate the personalization of questionnaires, work on customization and promotion, and ultimately deliver individualized services to suit the needs of diverse users. Besides client personalization, fintech companies must improve Robo-advisors' efficiency during market uncertainties. In their present form, Robo-advisors are unable to address customer grievances in case something goes wrong in the market. Financial advisory firms could also offer a hybrid service model that combines Robo-advisors and human advisors. The former provides standard portfolio advice, and the latter offers exceptional services during unusual events like market crashes, financial crises, and future uncertainty. AI can be utilized as a tool to enhance the capabilities of human advisers rather than replace them. When AI technologies are used, human advisors may concentrate on high-value jobs like developing connections with customers and giving tailored advice.

The development and spread of robo-advisory services in the financial industry frequently necessitate supportive regulatory frameworks. As the expert opined, with the technology advances, governments must amend or adopt new regulations to address the specific issues and possibilities provided by robo-advisory platforms. Policymakers must strike a balance between supporting innovation and safeguarding investors. Academicians must explore the laws governing Robo-advisory services across the globe and suggest recommendations to policymakers to foster the effective growth of robo-advisory services in the financial system. As customers' awareness and familiarity with Robo-advisory influence their desire to adopt the services, it is essential to address the potential users of Robo-advisory services. The researchers highly recommend that the customers seek information (e.g., news, reports, reviews, etc.) that demonstrates the service's features (e.g., advantages, limitations, profitability, convenience, etc.) and check for evaluations and opinions from other customers. Thus, it will help them establish realistic expectations regarding financial Robo-advisors, lowering perceived risk and boosting the likelihood of adopting such algorithm-based services. Regulators must initiate digital literacy programs to increase consumer awareness and confidence in robo-advisory services. Digital financial transformation and framing technology-friendly policies may further assist the diffusion of automated advisory services in the investment sector.

Conclusion

Among the diverse, innovative FinTech, Robo-advisors are of specific interest to investors due to their distinctive features. As opposed to other initiatives, Robo-advisors are based on AI-powered systems and are in the process of transforming investment advisory services in the future. Robo-advisors provide cost-efficient, disciplined, timely, goal-based, and bias-free financial advice to investors at any hour of the day. Even though Robo-advisors are in their infancy stage, there is an estimated vast market for them in the years ahead, especially with the advancement of digital technologies and the rise of online businesses. This adoption necessitates a more detailed study of potential users' views, intentions, and eventual acceptance of financial Robo-advisors.

In this light, the present study conducts a scoping review of the factors affecting the adoption of Robo-advisors worldwide. The study supplements current research on Robo-advisors by answering why and how people might vary in their readiness to use a Robo-advisor for investing decisions. Based on the review, seven significant themes were derived: perceived usefulness, perceived ease of use, trust, risk, prior knowledge and familiarity, behavioral biases, and demographic variables affecting the acceptance and adoption of financial Robo-advisors. The prime models adopted by researchers were TAM, DOI, and UTAUT. The study concluded by identifying the gaps in the current literature and suggesting to budding scholars the scope for further research.

Robo-advisory services in financial decision-making are considered incipient in most developing economies and thus can increase the consumer base and market share shortly. This study further provides recommendations to service providers, policymakers, and marketers for speedy diffusion and acceptance of algorithms for financial decision-making among the public, individualization of financial advice, and regulation of innovative business models, such as Robo-advisors, for sustainable growth and continued use.

Limitations of the Study

Robo-advisors are entering the mainstream financial advisory sector and gaining popularity among investors. Most of the studies reviewed are from developed economies, and individual perceptions differ in their strengths across borders. Therefore, future research must consider developing countries, as there is a bright future for Robo-advisory services in developing economies. To better analyze specific factors that contribute to Robo-advisory adoption, future research needs to include behavioral measures (such as current and past utilization of financial products, financial literacy, prior knowledge, intrinsic motivation, participation in household finance, etc.) to acquire a deeper understanding into the relationship between experience and acceptance. As merely intending to make use of technology does not often translate into real usage, follow-up studies to test Robo-advisors' actual acceptance and dissemination among investors remain an unexplored area for research.

Further, academics may research the elements influencing client retention in the automated advice industry to address the gaps in customer satisfaction. As trust is a crucial factor for technology adoption, academics may also construct theoretical models to better understand the aspects that influence trust in technology and recommend approaches to instil emotional confidence in the advice provided by algorithms. The authors further suggest that future researchers empirically test the framework developed in the study for technology adoption among various domains. Despite the limitations, we are assertive that the results of this study will provide insights to policymakers, service providers, and other scholars in extending future research and implementing effective policies for the promotion of Robo-advisory in the finance sector.

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