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TECHNOLOGY ADOPTION IN INVESTMENT AND FINANCE (SYSTEMATIC LITERATURE REVIEW)

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Abstract: The goal of this study is to examine significant trends, analyze the relationships between keywords, and uncover factors influencing technology adoption in investment and finance. Using a Systematic Literature Review (SLR) approach, this article gathers and analyzes data from relevant scientific publications on Google Scholar with keywords such as robo-advisor, TAM, TPB, individual investors, and financial technology. The results are visualized through three types of maps: the keyword relationship map, the temporal evolution map, and the heatmap using VOSviewer. The main findings indicate that trust and technology adoption are key factors in this research, with keywords like "investment," "investor," "trust," and "adoption" emerging as central topics. The temporal evolution map shows an increase in research related to "technology acceptance model (TAM)" and "robo advisor" in recent years, indicating a growing interest in understanding the adoption of new technology. The heatmap identifies areas of high research concentration on "adoption," "technology," and "investment" and highlights areas requiring further research.

Keywords: Technology Adoption, Investment, Finance, Robo Advisor, Technology Acceptance Model (TAM), Systematic Literature Review (SLR)

INTRODUCTION

The rapid development of information and communication technology has made the adoption of technology in the financial and investment sectors a critical research topic. New technologies like robo advisors, blockchain, and fintech have transformed how individuals and institutions manage and invest their assets. Understanding the factors influencing technology adoption is crucial in this context.

Robo-advisors are online platforms that offer automated investment management services with little to no human involvement. Their key benefits include reduced costs and greater accessibility when compared to conventional financial advisors. Despite these advantages, individual investors face several obstacles in adopting robo-advisors, particularly concerns surrounding trust and perceived risk. The Technology Acceptance Model (TAM) is a widely utilized framework for understanding how individuals adopt and use new technologies. According to TAM, the acceptance of technology is primarily driven by two factors: the perceived ease of use and the perceived usefulness of the technology.

This research aims to:

1. Identify key research trends in technology adoption in finance and investment sectors.
2. Analyze the relationships between frequently appearing keywords in related literature.
3. Offer a more comprehensive insight into the factors that impact the adoption of technology in this industry.
4. Highlight existing research gaps and offer recommendations for further research.

Based on these research objectives, this study explores several important research questions, including

1. What are the main trends in research on technology adoption in finance and investment sectors?
2. How are the relationships between key keywords?
3. What factors most influence technology adoption in this sector?

4. How have users' views on emerging technologies, such as robo-advisors and the Technology Acceptance Model (TAM), changed over time?

This research has broad significance from both theoretical and practical perspectives. Theoretically, it adds to the existing literature on technology adoption by offering a detailed analysis of the trends and factors influencing technology adoption in the finance and investment sectors. Practically, the findings can help financial service providers, technology developers, and regulators design more effective strategies to encourage the adoption of new technology.

LITERATURE REVIEW

The adoption of technology in the financial sector is frequently examined through several theoretical frameworks, one of the most prominent being the Technology Acceptance Model (TAM). Introduced by Davis in 1989, TAM suggests that the acceptance of technology is primarily determined by two key factors: perceived ease of use and perceived usefulness. Further studies by Venkatesh and Davis (2000) expanded TAM by including social and cognitive factors affecting technology adoption.

Financial robo-advisors are advanced versions of traditional financial advisors, leveraging technology as a core asset to provide personalized investment recommendations tailored to individual risk profiles. The roots of financial advising can be traced back to the 1950s in the United States, where personal financial advisors primarily served wealthy families. These advisors operated independently, delivering premium services to high-net-worth individuals. By the 1970s, U.S. financial advisors introduced discount brokers aimed at the middle class, offering services at lower fees compared to traditional advisors. These brokers only buy and sell orders, thus earning lower commissions.

During the 1990s, the advent of the World Wide Web (WWW) and increased internet accessibility had a profound effect on the financial sector. While online trading became theoretically more accessible, the majority of new investment opportunities were still primarily available to individuals focused on trading. As information technology advanced rapidly, it enabled greater connectivity between devices, quicker and easier access to information, and reduced transaction costs. These developments opened up new opportunities for potential investors and led to shifts in individual behavior (Sironi, 2016; Jung, Dorner, Glaser, & Morana, 2019).

Figure 1. History of Robo-Advisors



Source: Sironi (2016); Jung et al. (2019)

Robo-advisors were first introduced in 2008 and saw rapid growth in the U.S. and internationally by 2011 (Xue, Li & Pei, 2018). With advancements in Big Data and artificial intelligence (AI), the evolution of financial robo-advisors has accelerated significantly. According to Deloitte (2016), robo-advisors have progressed from version 1.0 to 4.0, incorporating new methodologies and increasingly sophisticated technologies.

Robo advisors are significant technological innovations in investment management. They offer automated investment management solutions at lower costs than human advisors. However, adopting robo advisors still faces user trust challenges. Research by Belanche, Casaló, Flavián & Schepers (2019) shows that trust is a key factor in adopting robo advisors. This study found that trust in technology and risk perception play vital roles in investors' decisions to use robo advisors. Research by Gefen, Karahanna, and Straub (2003) states that online trust is significantly influenced by risk perception and perceived usefulness. This study shows that factors such as technology reliability, data security, and process transparency play important roles in building user trust.

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RESEARCH METHODS

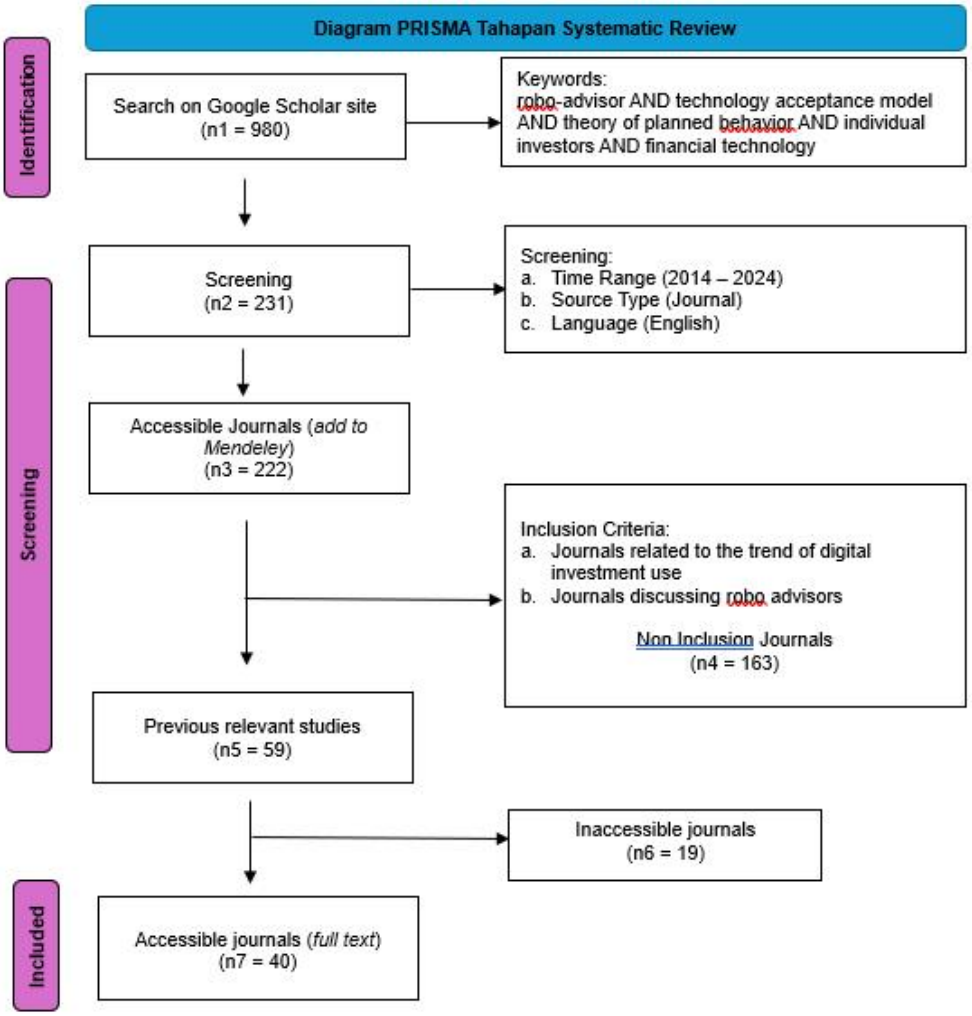
This study employs a Systematic Literature Review (SLR) approach to identify, assess, and synthesize relevant literature regarding technology adoption within the finance and investment sectors. SLR is chosen because it allows researchers to systematically collect and analyze existing literature, ensuring that all relevant studies are considered and reducing bias in the research process.

The first stage in SLR is collecting relevant scientific articles from the Google Scholar database using the keywords "robo-advisor, technology acceptance model, theory of planned behavior, individual investors, financial technology." To refine the search, the Prisma framework is applied. Inclusion and exclusion methods are implemented to screen the topics of interest. Screening is conducted to filter content closest to the discussed topic based on the article titles and abstracts reviewed. Articles related to robo advisors are included. For further study, full-access articles are required. Finally, bibliometric methods are applied to determine the progress, novelty, and originality of the research conducted. In addition to the Prisma framework, VOSviewer is also used to analyze the relationships between keywords, temporal trends, and research concentration areas.

RESULTS AND DISCUSSION

Applying the Prisma framework results in Figure 2. Using the keywords, 980 articles were generated (n1). The period reviewed is from 2014 to 2024. The document type is articles in the final stage of publication and published in journals using English as the communication language. A total of 231 articles (n2) were generated from the screening stage. Only 222 articles (n3) could be accessed and added to the Mendeley library.

Figure 2. PRISMA Diagram Stages of Systematic Review



Source: Figure created by Author

All 222 articles were reviewed based on their titles and abstracts. Of these, only 59 (n5) contained discussions on "digital investment usage trends" or "robo advisors." Due to subscription sites, only 40 articles (n7) were explored further, while 19 articles (n6) were inaccessible.

Table 1 presents the number of articles published in various journals alongside their total citations. The Journal of Risk and Financial Management and the International Journal of Bank Marketing published the highest number of articles, each contributing 2 articles (4.76%). However, the Journal of the Academy of Marketing Science garnered the most citations, with a total of 161.

Table 1. Number of Articles and Citations by Journal

No	Journal	Total Articles	Total Citations
1	*Journal of the Academy of Marketing Science*	1	161
2	*Journal of Services Marketing*	1	99
3	*Journal of Interactive Marketing*	1	85
4	*Journal of Risk and Financial Management*	2	64
5	*Journal of Financial Counseling and Planning*	1	62
6	*Journal of Financial Econometrics*	1	51
7	*Journal of Financial Services Research*	1	49
8	*Academic Journal of Science and Technology*	1	44
9	*Journal of Service Theory and Practice*	1	33
10	*Asia Pacific Journal of Marketing and Logistics*	1	29
11	*Baltic Journal of Management*	1	25
12	*Journal of Financial Reporting and Accounting*	1	25
13	*Journal of Business Research*	1	23
14	*Journal of Behavioral and Experimental Economics*	1	22
15	*Journal of Electronic Commerce Research*	1	21
16	*International Journal of Bank Marketing*	2	19
17	*Journal of Corporate Law Studies*	1	14
18	*Journal of Finance Issues*	1	12
19	*IDRBT Journal of Banking Technology*	1	11
20	*SSRN Electronic Journal*	1	11
21	*Journal of Governance and Regulation*	1	9
22	*Journal of Entrepreneurship, Business and Economics*	1	7
23	*Journal of Financial Economics (JFE)*	1	6
24	*Journal of Innovation Management*	1	6
25	*Journal of Financial Services Marketing*	1	5
26	*Equilibrium Quarterly Journal of Economics and Economic Policy*	1	5
27	*International Journal of Sociology and Social Policy*	1	4
28	*Journal of Indonesian Economy and Business*	1	4
29	*Journal of Physics: Conference Series*	1	4
30	*Journal of Positive School Psychology*	1	3

No	Journal	Total Articles	Total Citations
31	*Journal of Global Business and Technology*	1	2
32	*Australasian Marketing Journal*	1	1
33	*Accounting and Business Information Systems Journal*	1	0
34	*Australasian Accounting, Business and Finance Journal*	1	0
35	*Journal of Applied in Business Management and Accounting*	1	0
36	*Journal of Survey in Fisheries Sciences*	1	0
37	*Environment-Behaviour Proceedings Journal*	1	0
38	*WSB Journal of Business and Finance*	1	0
	Total	**40**	

Source: Table compiled by Author

Table 2 presents the citation count for each individual article. The article by C. Hildebrand & A. Bergner titled "Conversational Robo Advisors As Surrogates Of Trust: Onboarding Experience, Firm Perception, And Consumer Financial Decision Making" received the most citations, with 161 citations.

Table 2. Citations by Article

No	Author (Year)	Number of Citations
1	Hildebrand, C., & Bergner, A. (2020)	161
2	Zhang, L., Pentina, I., & Fan, Y. (2021)	99
3	Lourenço, C. J. S., Dellaert, B. G. C., & Donkers, B. (2020)	85
4	Fan, L., & Chatterjee, S. (2020)	62
5	Alsabah, H., Capponi, A., Ruiz Lacedelli, O., & Stern, M. (2021)	51
6	Anshari, M., Almunawar, M. N., & Masri, M. (2022)	50
7	Oehler, A., Horn, M., & Wendt, S. (2022)	49
8	Huang, Z., Che, C., Zheng, H., & Li, C. (2024)	44
9	Wexler, M. N., & Oberlander, J. (2020)	33
10	Yeh, H. C., Yu, M. C., Liu, C. H., & Huang, C. I. (2023)	29
11	Beltramini, E. (2018)	25
12	Nourallah, M., Öhman, P., & Amin, M. (2023)	25
13	Nourallah, M. (2023)	23
14	Back, C., Morana, S., & Spann, M. (2023)	22
15	Roh, T., Xiao, S., & Il Park, B. (2023)	21
16	Huang, R. H., Wang, C. C., & Zhang, O. X. (2022)	14
17	Filiz, I., Judek, J. R., Lorenz, M., & Spiwoks, M.	14

No	Author (Year)	Number of Citations
	(2022)	
18	Aw, E. C. X., Leong, L. Y., Hew, J. J., Rana, N. P., Tan, T. M., & Jee, T. W. (2024)	12
19	Kim, S. D., Cotwright, M., & Chatterjee, S. (2019)	12
20	Megargel, A., Shankararaman, V., & Fan, P. C. T. (2018)	11
21	Bianchi, M., & Brière, M. (2021)	11
22	Kraiwanit, T., Jangjarat, K., & Atcharanuwat, J. (2022)	9
23	Ruslan, R. A. H. M., Ibrahim, M. A., & Abd Hamid, N. H. (2022)	7
24	Chou, S. Y., Lin, C. W., Chen, Y. C., & Chiou, J. S. (2023)	7
25	Reher, M. & Sokolinski, S. (2024)	6
26	Salampasis, D. (2017)	6
27	Eren, B. A. (2023)	5
28	Piotrowski, D., & Orzeszko, W. (2023)	5
29	Wexler, M. N., & Oberlander, J. (2023)	4
30	Ashrafi, D. M. (2023)	4
31	Potdar, A., & Pande, M. (2021)	4
32	Km Poornima, M., & Chitra, S. (2022)	3
33	Ashrafi, D. M., & Kabir, M. R. (2023)	2
34	Roongruangsee, R., & Patterson, P. (2023)	1
35	Alam, A. F., & Achjari, D. (2020)	0
36	Vijaya, C., Hati, K., & Thenmozhi, M. (2024)	0
37	Fahruri, A. (2023)	0
38	Ramesh, K. P., Mathew, N., Amudha, R., Sudhahar, J. C., & Rangaswamy, E. (2023)	0
39	Abdul Manaf, S. M., Ismail, M. K. A., & Zakaria, S. (2023)	0
40	Mrkývka, P., & Šiková, Z. (2023)	0

Source: Table created by Author

The VOSviewer results illustrate the connections between key concepts related to technology adoption within the context of investors and financial services. The primary topics identified in the data include keywords such as "investor," "investment," "technology," "adoption," and "technology acceptance model (TAM)". There are three colors produced, indicating three clusters or sub-topics in fintech research.

Figure 3 reveals a connection between investors, investment instruments, and robo-advisors. Additionally, a relationship is observed between technology and the technology acceptance model. A strong link between investors and trust is also evident, highlighting the crucial role that trust plays in the adoption of financial technology. For further clarity, each cluster formed on this map is discussed in Table 3. There are three

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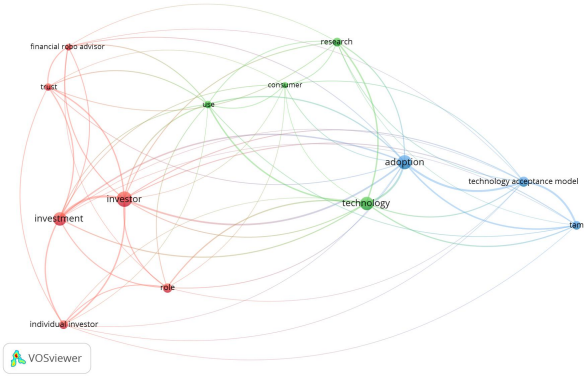
keyword clusters identified and interconnected with each other. Red, green, and blue represent the first, second, and third clusters, respectively.

Cluster 1 consists of six keywords: "Consumer," "Impact," "Research," "Role," "Technology," and "Use." This indicates that research in this cluster focuses on the role of technology and its impact on consumers and how the technology is analyzed through various studies. Cluster 2 consists of five keywords: "Financial robo advisor," "Individual investor," "Investment," "Investor," and "Trust". This suggests that the research in this cluster centers on the use of financial robo-advisors by individual investors and examines how trust affects their investment decisions. Cluster 3 consists of three keywords: "Adoption," "TAM," and "Technology acceptance model." This indicates that research in this cluster focuses on technology adoption and the use of the Technology Acceptance Model (TAM) to explore the factors that influence the acceptance of new technologies.

Figure 3. Network Visualization by VOSViewer



Source: VosViewer

Table 3. Clusters Formed Based on Keywords

Key Words	Links	Total link strength	Occurrences
Cluster 1 (6 items)			
Consumer	9	14	10
Impact	7	22	14
Research	10	28	18
Role	10	26	21
Technology	11	57	45
Use	12	35	14
Cluster 2 (5 items)			
Financial robo advisor	8	19	11
Individual investor	9	24	18
Investment	12	53	42
Investor	13	67	54
Trust	8	25	14
Cluster 3 (3 Items)			
Adoption	13	78	49
TAM	8	36	18
Technology acceptance model	10	44	27

Source: Table created by Author

From Figure 4, the research timeframe spans from 2021 to 2022. The color of the keywords indicates the period when the topic was widely researched or popular. The color scale at the bottom shows that blue indicates research conducted around 2021, while yellow indicates more recent research around 2022. The

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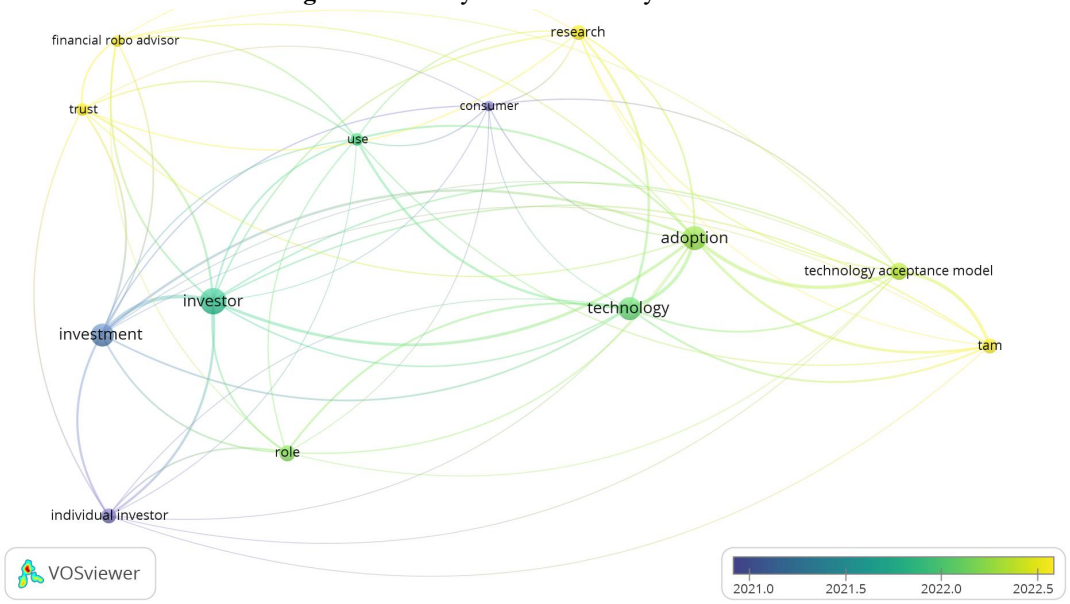
keywords "TAM" and "Technology acceptance model" are yellow, indicating that this topic has been researched more recently. The term “robo advisor” is also relatively new, emerging around 2022.

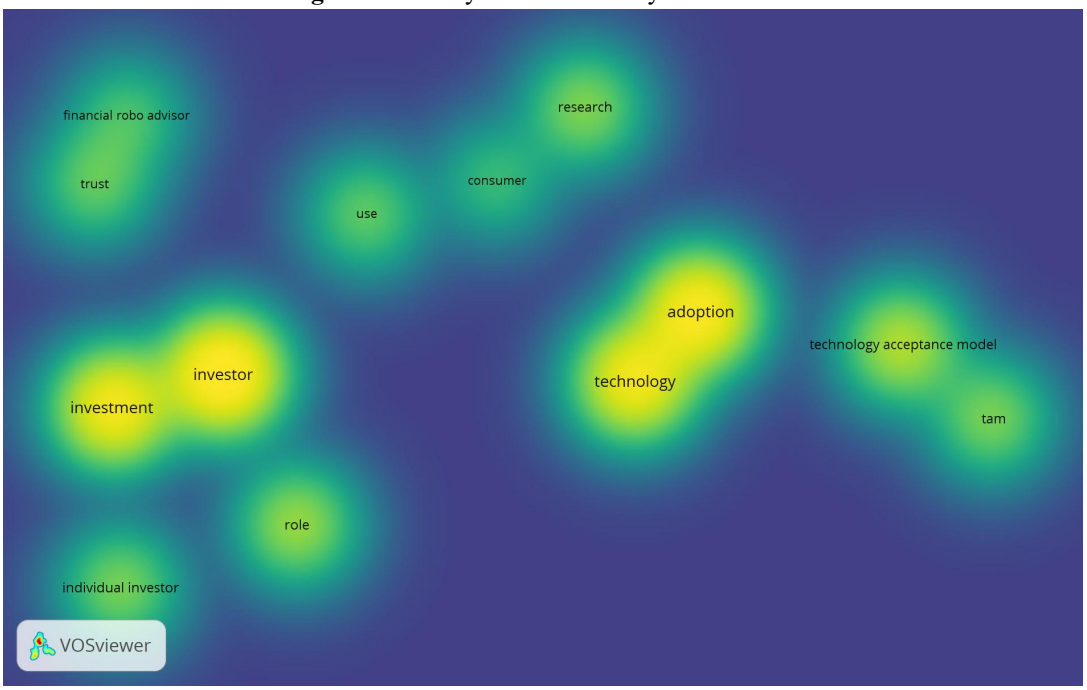
Figure 5 shows the density or frequency of keyword occurrences in research. Yellow indicates areas of high density, meaning the keywords in these areas frequently appear in research; green indicates moderate density areas, and blue indicates low-density areas. This map shows that “technology” and “adoption” have many studies on how new technology is accepted in the financial context, while “financial robo-advisor” and “individual investor” are less discussed in the literature.

Figure 4. Overlay Visualization by VOSViewer



Source: VosViewer

Figure 5. Density Visualization by VOSViewer



Source: VosViewer

Based on 40 studies that discuss the factors affecting the adoption and perception of robo-advisors in financial services, here are some explanations related to robo-advisors. Research by Hildebrand & Bergner (2020) demonstrates that conversational robo-advisors have the potential to enhance trust among users and improve consumer perceptions of the company, which ultimately influences consumer financial decisions.

Lourenço et.al (2020) stated that the type of company and Perceived expertise plays a crucial role in influencing consumer acceptance of financial advice provided by robo-advisors. Consumers are more inclined to trust and follow advice from robo-advisors from companies with a high reputation in the field of financial expertise. The findings of Nourallah et.al (2023) show that public information and information seeking through social media are closely linked to the development of initial trust, which subsequently affects behavioral intentions to use robo-advisors. In another study, Nourallah, M. (2023) found that trust propensity, performance expectancy, and hedonic motivation are important predictors of initial trust in two countries (Malaysia and Sweden). Initial trust significantly influences behavioral intention to use a robo-advisor. There are cultural differences in the influence of trust propensity on initial trust, with significant individualism in Malaysia and significant uncertainty avoidance in Sweden. A study by Chou et.al (2023) concluded that the intangible value of banks is very important in the adoption of robo-advisors by customers. Trust in banking institutions and financial consultants is a major factor influencing intangible value. In addition, this intangible value influences customers' willingness to adopt robo-advisors, especially at lower investment levels. The study also highlights the importance of hybrid models that combine robo-advisor services with traditional banking services to increase the acceptance of this technology among consumers.

Zhang et.al (2021) explained that consumers tend to trust and use the services of financial advisors with high expertise more than robo-advisors. However, there is no significant difference between low expertise advisors and robo-advisors when it comes to performance expectations and the intention to use their services. Alsabah et.al (2021) revealed that robo-advisors can improve investor performance by learning their risk preferences over time and correcting investors' errors in portfolio selection. This approach can reduce costs and errors that are usually associated with manual investment decision making by investors.

Fan & Chatterjee (2020) stated that factors such as subjective advanced investment knowledge, basic financial knowledge, investment risk tolerance, and credit card comparison practices are positively related to the likelihood of robo-advisor adoption. Conversely, objective basic financial knowledge and objective advanced investment knowledge are negatively correlated to robo-advisor adoption. Oehler et.al (2022) also explained that investors with higher financial literacy and investment experience tend to be more open to using robo-advisors. Alam & Achjari (2020) stated that financial knowledge, perceived usefulness, confirmation, and satisfaction positively influence the intention to continue using robo-advisors as an investment tool in Indonesia. Vijaya et.al (2024) showed that a portfolio model based on automated security risk assessment and SB factors can produce better investment portfolios for tech-savvy retail investors.

Yeh et.al (2023) proposed that all variables in the UTAUT model— effort expectancy, performance expectancy, social influence, and facilitating conditions— positively and significantly affect both attitudes and behavioral intentions to adopt robo-advisors. Beltramini, E. (2018) found that robo-advisor adoption shifts vulnerability from the market to the machine, making users dependent on technology and altering the way they engage with financial markets. Roh et al. (2023) confirmed the proposed hypotheses concerning the direct and indirect effects of factors like effort expectancy, performance expectancy, social influence, facilitating conditions, perceived security, and perceived privacy on users' attitudes toward robo-advisors and their intentions to adopt fintech services. Most of these effects are indirect, mediated by attitude, trust, and facilitating conditions. Ruslan et.al (2022) stated that perceived ease of use is a significant factor in the decision to use a robo-advisor. Optimism and technological innovation positively influence the intention to use a robo-advisor, while technological inconvenience and insecurity negatively affect this intention. Eren, B. A. (2023) showed that performance expectations, facilitating conditions, social influence, financial risk tolerance, and trust are the main factors influencing the intention to use a robo-advisor in personal retirement investment in Turkey. Roongruangsee & Patterson (2023) showed that high performance expectations and technological readiness increase psychological comfort, while suspicion of human advisors also encourages clients to feel more comfortable with robo-advisory technology.

Huang et.al (2024) found that frequent adjustments in robo-advisor usage may hinder the achievement of long-term investment goals. They highlighted the importance of transparency and user-friendly interaction

design to enhance user trust. Findings by Kim et.al (2019) showed that robo-advisor users are typically younger, more willing to take risks, and highly confident in their financial knowledge. Although these users have lower objective financial literacy, they tend to make independent investment decisions and show a strong preference for diversified investment products. Reher & Sokolinski (2024) noted that robo-advisors impact not only wealthy investors who already have access to professional managers but also broaden access for less wealthy investors by lowering minimum account thresholds. By eliminating these barriers, participation increases, as less wealthy investors have a high demand for advanced wealth management services.

Huang et.al (2022) concluded that Hong Kong's robo-advisor regulation has significant strengths in some aspects but also faces challenges that require further attention. This regulation has enhanced investor protection while encouraging innovation. Piotrowski & Orzeszko (2023) discovered that the use of financial products did not have a significant effect on the decision to adopt robo-advisory services in banking. Instead, the willingness to embrace robo-advisory is more strongly influenced by openness to technological innovation and confidence in the advantages of AI, as well as experience in using AI technology in banking services. Mrkývka & Šiková (2023) stated that the EU's technology-neutral approach allows the same rules to be applied to all investment firms, regardless of the use of digital tools and automation. Although there are additional regulations for robo-advisory, this additional regulatory burden is not significant and reflects the proportionality obligation for existing business models.

Anshari et.al (2022) stated that digital twins can transform and optimize intelligent financial advisory services, providing significant added value to users' personal financial management. Salampasis, D. (2017) revealed that the fund management industry is influenced by the application of new technologies that require innovation in terms of processes and outcomes to create investment tools and vehicles that address global challenges. The rise of hybrid consulting models (which integrate both human expertise and AI capabilities) is expected to bring conceptual changes in the SRI market and democratize this type of investment for good purposes. Piotrowski & Orzeszko (2023) concluded that attitudes towards technological innovation, trust in bank business ethics, and experience in using modern technology are more decisive in increasing the acceptance of robotic advisory services. Fahruri, A. (2023) stated that usability, trust, cost, security, risk, and social influence are important factors for the adoption of robo advisors in Indonesia. Regulators are needed to support and establish clear regulations to ensure that robo advisor services operate in accordance with applicable regulations. Ramesh et.al (2023) concluded that AI in robo advisor services has yielded very positive results. The advanced capabilities of AI allow robo-advisors to play a crucial role in the future of financial services, helping investors manage their investments at low cost. While perceptions of robo advisor platforms differ by gender, perceptions and adoption of platforms are not significantly affected by age. Hybrid models (Robo plus Human) can help meet investment needs as investors mature in their investment journey.

Kraiwanit et.al (2022) concluded that factors such as, amount invested in financial instruments, average monthly income and investment knowledge significantly influence the acceptance of robo-advisors among Thai investors. Providing information on the benefits, drawbacks, and risks of robo-advisors is needed to improve the understanding and acceptance of this technology among investors. Abdul Manaf et al. (2023) concluded that the adoption of robo-advisory services is shaped by a combination of individual factors, platform-specific elements, and market conditions. In Malaysia, robo-advisory adoption is still in its early phases, and there is a scarcity of literature addressing the factors influencing adoption among young investors. Back et.al (2023) found that robo-advisors can improve investment decisions by reducing the disposition effect, particularly through the provision of unbiased advice. However, incorporating social design elements into robo-advisors has the potential to create psychological barriers for investors to seek advice, thereby increasing the disposition effect.

Wexler & Oberlander (2020) revealed that robo-advisors combine algorithmic authority with cost-effective professional services, thereby disrupting the traditional financial services market. Wexler & Oberlander (2023) further explained that robo-advisors (RA) signify the integration of programmed and commercialized professional expertise in a highly competitive environment, a model that is likely to be adopted in other professional service sectors. RA shows that programmed and automated professional advice can succeed in a competitive market by reducing costs and attracting attention through algorithmic authority. In the sociology of professions, RA signifies a shift from reliance on certified professionals to algorithmic authority and continuously updated big data, which creates new challenges for professionals in

various fields. Filiz et.al (2022) stated that robo-advisors have great potential to provide effective portfolio management solutions at a low cost, but aversion to algorithms hinders their adoption. Overcoming this reluctance is a critical challenge to increasing the adoption of this technology in asset management. Potdar & Pande (2021) concluded that ARIMA is the most effective algorithm for stock price forecasting in the context of robo-advisory compared to other algorithms tested.

Research by Aw et.al (2024) shows that human attributes in robo-advisors can increase perceptions of fairness and reduce privacy and intrusion concerns, which ultimately reduces resistance to robo-advisors.

Megargel et.al (2018) stated that SOA (Service-Oriented Architecture) maturity has a positive impact on banks' ability to undergo digital banking transformation. Banks with mature SOA architecture tend to be more flexible and faster in bringing new digital banking products and services to market.

Bianchi & Brière (2021) concluded that robo-advising can significantly affect investor behavior, increasing attention, trading activity, and risk-adjusted returns, especially for small investors. This suggests that robo-advisors can serve as a valuable tool to enhance financial inclusion and improve financial outcomes for less experienced and less wealthy investors.

Ashrafi (2023) stated that relative advantage and perceived innovation positively impact on perceived value and intention to adopt robo-advisors. Complexity negatively impact on perceived value and intention to adopt. Ashrafi & Kabir (2023) found that perceived value is shaped by factors such as anthropomorphism, perceived enjoyment, and perceived performance, while perceived risk is influenced by trust, complexity, and perceived security. Both perceived value and perceived risk significantly affect users' behavioral intentions. The findings also suggest that innovation resilience plays a crucial role in moderating the relationship between perceived value and users' behavioral intentions to adopt robo-advisor services.

CONCLUSIONS AND SUGGESTIONS

Studies show that adoption and use of robo-advisors are influenced by a variety of factors, including trust, financial literacy, regulation, socio-psychological factors, demographics, and technology. Robo-advisors have great potential to improve investment performance and financial inclusion, although challenges such as algorithmic avoidance and risk perception still need to be addressed.

Key trends in technology adoption research in the financial and investment sector include the growing interest in the use of new technologies such as robo-advisors and TAM. The study shows that trust and technology adoption are key topics. The temporal evolution map shows an increase in research on the “technology acceptance model (TAM)” and “robo advisors” in recent years, indicating a growing interest in understanding the adoption of new technologies in the financial and investment sector. The study uses the VOSviewer visualization tool to map the relationships between key keywords. It is found that the keywords “investor”, “investment”, “technology”, “adoption”, and “technology acceptance model (TAM)” are key topics. There are three groups of keywords: the first group focuses on the role of technology and its impact on consumers and the analysis of technology use (keywords: “Consumer”, “Impact”, “Research”, “Role”, “Technology”, “Use”); the second cluster focuses on the use of robo-financial advisors by individual investors and the importance of trust in investment decisions (keywords: “Robo-financial advisors”, “Individual investors”, “Investment”, “Investors”, “Trust”); and the third cluster focuses on technology adoption and the analysis of factors influencing technology acceptance using the technology acceptance model (keywords: “Adoption”, “TAM”, “Technology acceptance model”).

Several key factors influencing technology adoption in the financial and investment sectors include:

1. Trust in technology and risk perception play a significant role in investors' decisions to use robo-advisors.
2. Consumer trust and acceptance of robo-advisors is influenced by the company's reputation and the expertise it possesses.
3. Financial literacy and investment experience affect the acceptance of new technology.
4. Performance expectations, social influence, and security perception positively affect attitudes and behavioral intentions to use robo-advisors.
5. Robo-advisor users tend to be younger, more risk-taking, and have lower objective financial literacy.
6. Regulations and trust in the business ethics of banks influence technology acceptance.

7. Technological innovation, data security, and process transparency play important roles in building user trust.

User perceptions of new technologies such as robo-advisors and the Technology Acceptance Model (TAM) evolve over time with increased research and understanding of the factors influencing the acceptance of these technologies. Studies show that trust and perceived usefulness play crucial roles in technology acceptance. More recent research indicates increased interest and adoption of robo-advisors, with users becoming more confident in this technology as financial literacy and technology reliability improve. Hybrid models that combine robo-advisor services with traditional banking services are also beginning to be accepted to enhance the acceptance of this technology among consumers.

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