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FINANCIAL ROBO-ADVISOR: LEARNING FROM ACADEMIC LITERATURE

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ABSTRACT: Financial Robo-Advisor is the technology that integrates machine learning and self-identification to determine investment decisions. This study explores the financial robo-advisor based on bibliometric analysis and a systematic literature review. The method used three steps: determining the keyword, a bibliometric analysis of literature metadata using VOSviewer, and collecting and analysing the articles. The bibliometric analysis results show five cluster keywords in the network visualisation. The robo-advisor connects to other keywords, i.e., investment, fintech, and artificial intelligence. Furthermore, the systematic literature review shows that the pool of articles are divided into seven research objectives: (1) Law, Regulation, and Policy; (2) Investment Literate and Education; (3) Offered Services; (4) Present Risk-Portfolio Matching Technology; (5) Optimal Portfolio Methods; (6) Human-Robo Interaction; (7) Theoretical Design and Gap.

Keywords: Finance; Robo-Advisor; Systematic Literature; Bibliometric Analysis

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INTRODUCTION

The term "Robo" in financial investment may refer to robotic-based trading or advisor in the applications that use a specific algorithm to automate the financial transaction based on time, price, quantity, and other economic attributes that emerge to provide a new opportunity for potential investors (Baek et al., 2020). It triggers the shifting of individual behaviour as the effect of information technology develops rapidly and give opportunities to build connectivity between gadgets, faster and easier access to information, and cheaper transaction costs. On the other hand, a robo-advisor may present as the advanced level of the traditional financial advisor by maximising its uses of technology as its underlying asset and personalised investment offering based on risk profile. Thus, robo-advisor can be used for beginner investors to start investing is suitable for investors with extra saving funds to invest and tendency to diversify their assets.

Today, financial Robo-Advisor has become a new trend that increase investor numbers, especially for emerging countries such as Indonesia. Many financial applications are booming to encourage investors, especially young millennials by offering many facilities, easiness, and personal advisors. The technology in the robo-advisor integrates the financial technology and portfolio management process to provide a less emotional decision-making process and a wide range of services based on opportunities and risks. Furthermore, the Robo-Advisor also offers a balanced decision and applies behavioural strategies to frame and select the profitable options that make the user more confident to invest in financial assets. However, several scandals in the creation and marketing of these tools have placed them under intense scrutiny (Buchanan & Wright, 2021), with several celebrity endorsers are jailed and tools are terminated (Source: Aljazeera, 2022).

These phenomenon urges the creation of comprehensive study about the current state-of-the art of financial robo-advisor. This study, thus, aims to explore the financial robo-advisor literatures based on a systematic literature review and bibliometric analysis using the Scopus metadata and VOSviewer software.. This research is structured by providing an introduction to the research phenomenon. It will then present the literature review regarding the current knowledge on the issue. The research method is constructed for the study's approach as a bridge to present the emerging results. Finally, the discussion and potential future researches are provided.

THEORETICAL REVIEW

Financial Robo-Advisor is the advanced level of the traditional financial advisor, which uses technology as their underlying asset and personalised investment offering based on risk profile. The history of financial advisors began in the 1950s in the U.S. as the leading market for financial advisory. At that time, only wealthy families who have personal financial advisors. The personal financial advisor was very single-handed and provided well-grounded services targeting *ultra-high-net-worth individuals*. In the 1970s, financial advisories in the

U.S. introduced discount brokers who specialised in the middle class. It offers cheaper costs than traditional financial advisors. They were only in charge of buying and selling orders by earning a reduced commission.

In the 1990s, the World Wide Web (WWW) was introduced, and the accessibility of the internet significantly impacted the financial industry. Online trading can be accessed theoretically, but new investment opportunities are mostly limited to trading-orientated individuals. When information technology developed rapidly, it gave opportunities to build connectivity between gadgets, faster and easier access to information, and cheaper transaction costs. Thus, this trend emerges to provide a new opportunity for potential investors and shifts individual behaviour (Sironi, 2016, pp.66-68; Jung et al., 2019).

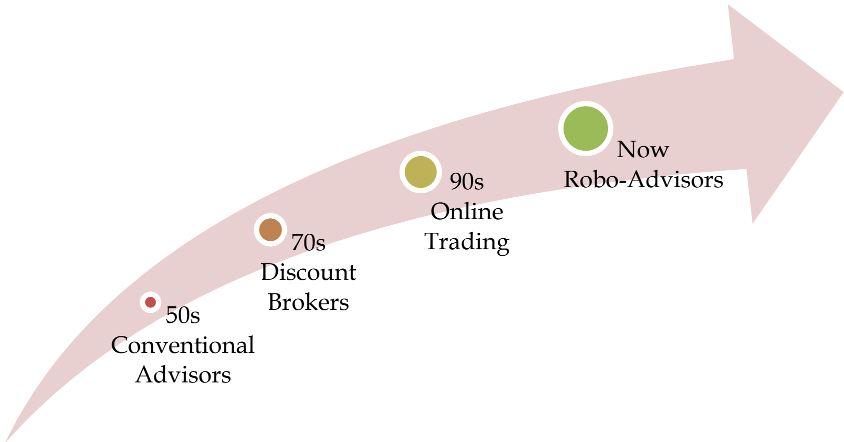

Figure 1. Financial Robo-Advisor Milestone
Source: Sironi (2016); Jung et al. (2019)

Robo-Advisor first appeared in 2008 and accelerated in the U.S. and other countries in 2011 (Xue et al., 2018). When Big Data and A.I. snowball, the evolution of financial Robo-Advisor explodes. The reports of Deloitte (2016) highlights the development of the robo-advisor from 1.0 to 4.0 with the new method and use of more sophisticated technology.

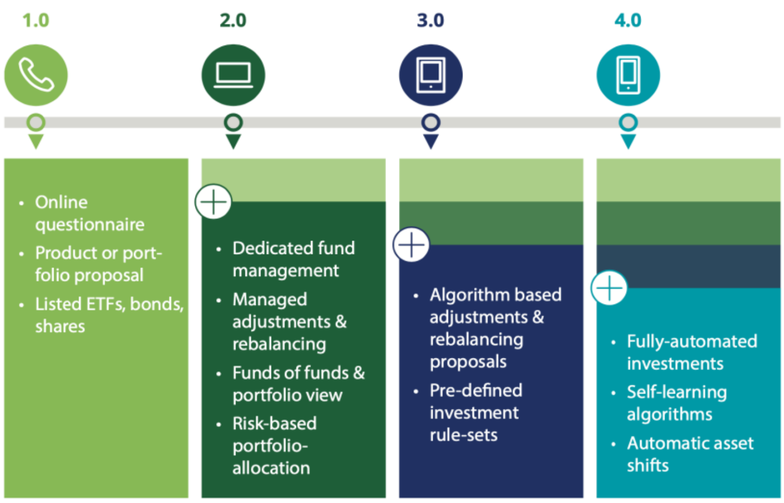

Figure 2. Robo-Advisory Evolution: Digital Wealth Management
Source: Deloitte (2016)

- Robo-Advisor 1.0 offers the listed investment products after the clients answer a questionnaire to filter suitable options. Then, the clients use their accounts to buy and manage their products based on their portfolios.
- Robo-Advisor 2.0 uses a semi-automatic approach, where the investment manager organises the asset allocation, oversees the investment algorithm, and defines rule sets.
- Robo Advisor 3.0 uses algorithms to monitor and adjust pre-defined investment strategies, but the professional fund manager supervises the final oversight of investment.
- Robo Advisor 4.0 uses sophisticated self-learning Artificial Intelligence investment algorithms in which the changing market condition and investment needs can adjust the investor's asset classes in real-time.

METHODOLOGY

We select the publications from the Scopus database since its first appearance up to 2021, and 105 are obtained.

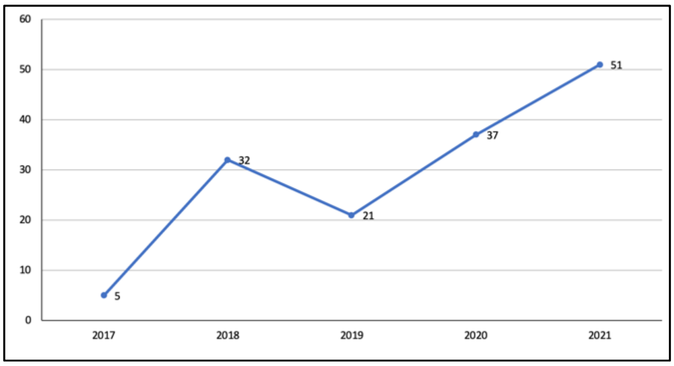

Figure 3. Number of Financial Robo-Advisor Articles

The framework analysis of this study uses the three-step method, as shown in figure 4. *The first step* is determining the research scope. In this step, the research focuses on exploring the financial robo-advisor article by using a specific keyword, *"robo advi*"* OR *"robo-advi** and *"financ*"*. The database shows 146 documents from 2017 to 2021, see the detail in figure 5.

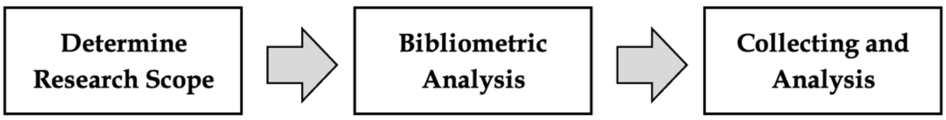

Figure 4. Literature Framework

The second step is bibliometrics analysis using VOSViewer software. Before starting this step, the researchers ensure the data is trimmed from double keywords and punctuation. The process can be done using spreadsheet software such as Microsoft Excel to extract the data. After the metadata is clean, it can be processed using VOSViewer, which can map the pattern, show the research scope position, and show the literature clustering by dividing it into different colours.

The VOSViewer software shows the three model networks, which consist of First, *Network Visualization* is used to identify the connection between word and their relationship. Second, *Overlay Visualization* determines the number of articles by year. Then Third, *Density Visualization* is used to show the word density. In this step, the bibliometric analysis only focused on connecting keywords between articles and conference papers with similar themes.

The third stage is collecting and analysing the articles by only focuses on articles and conference papers. The authors then mapped the emergence results.

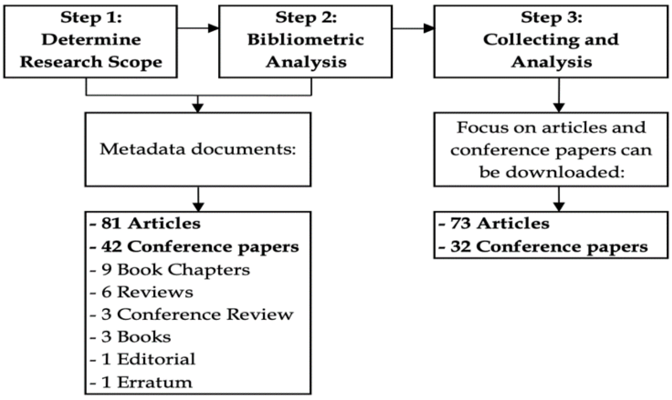

Figure 5. Number of Documents for Analysis

RESULTS AND DISCUSSION

Bibliometric Analysis

Our initial mapping, using Bibliometric analysis, shows the network clustering based on keyword frequency, historical literature development, and its density visualisation is presented in figures 6, 7, and 8 below. The network mapping of the financial robo-advisor study consists of 69 items, 722 links, and a full link by the strength of 1.362 connections. The circle size represents the keyword frequency in the literature.

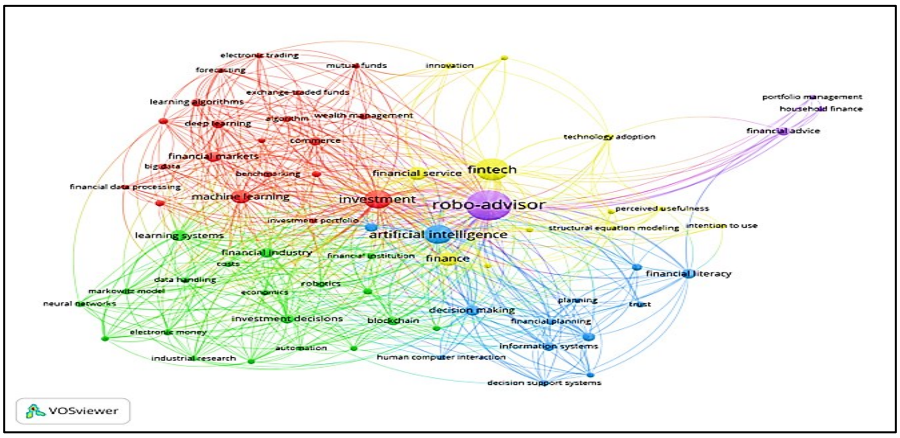

Figure 6. Network Visualisation of Financial Robo-Advisor

Figure 6 shows that robo-advisor closely relates to investment, fintech, and artificial intelligence. This is possible since fintech and artificial intelligence supports robo-advisor in the investment process. Figure 7 provides the historical presentation of the study of robo-advisor.

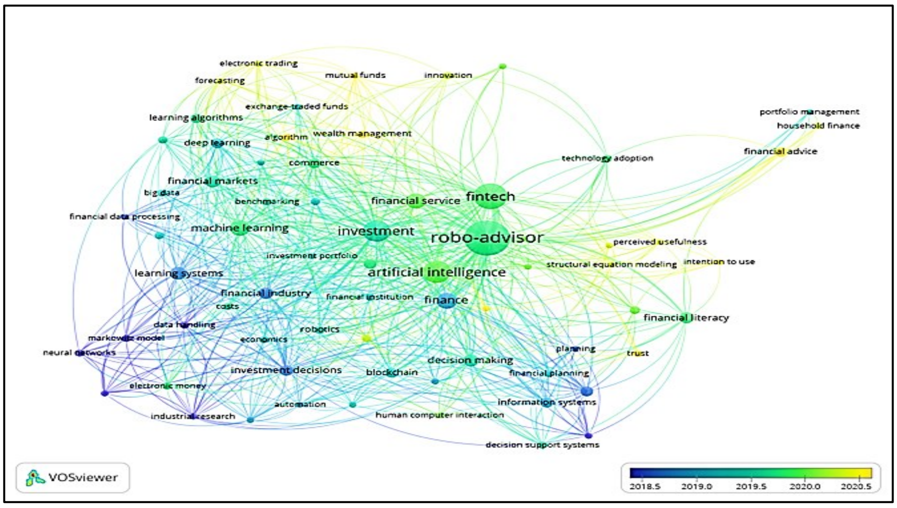

Figure 7. Robo-Advisor History in Literature

It initially started in 2018, with the Markowitz model to advise portfolio and the beginning of financial data processing to develop the financial instrument. In 2019, the research broadened to use machine learning and learning algorithms to construct more advanced asset allocation and portfolio optimisation. The 2020s marks the latest discussion evolved to financial advice, which supports human-robot interaction, impacting trust and intention to use the robo-advisor technology.

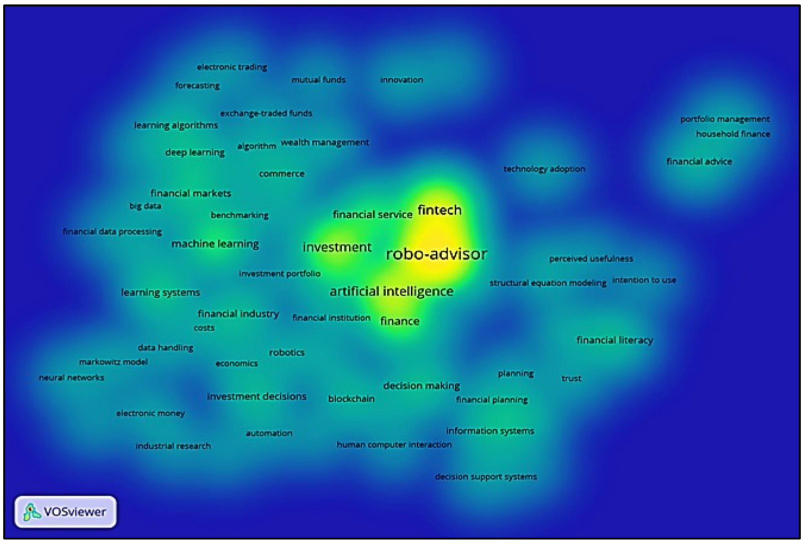

Figure 8. Density Visualisation

Figure 8 shows the study's field density visualisation; the darker the colour, the less the keyword is used, and thus, more opportunity of future researches. Based on the network visualisations above, we document five research clusters in Table 1. Cluster 1 discusses the investment theme, while Cluster 2 learning systems theme, Cluster 3 artificial intelligence theme, Cluster 4 fintech theme, and Cluster 5 robo-advisor theme.

Table 1. The Clustering Colors of Financial Robo-Advisor Network

Cluster	Keywords	Colour
Cluster 1 (20 items)	Algorithm; Asset allocation; Benchmarking; Big data; Cluster analysis; Commerce; Deep learning; Electronic trading; Exchange-traded fund; Financial data processing; Financial markets; Forecasting; Investment; Investment management; Investment portfolio; Learning algorithms; Machine learning; Mutual funds; Portfolio optimization; Wealth management	Red
Cluster 2 (19 items)	Automation; Blockchain; Costs; Data analysis; Data handling; Economics; Electronic money; Financial industry; Financial institution; Financial instruments; Industrial research; Investment decision making; Investment decisions; Knowledge management; Learning systems; Markowitz model; Neural networks; Robotics; Service industry	Green
Cluster 3 (13 items)	Artificial intelligence; Decision making; Decision support system; Financial decisions; Financial literacy; Financial planning; Human-computer interaction; Information systems; Information use; Planning; Risk assessment; Surveys; Trust	Blue
Cluster 4 (13 items)	Asset management; Design/methodology/approach; Finance; Financial advisors; Financial service; Fintech; Innovation; intelligent robots; Intention to use; Perceived usefulness; Sales; Structural equation model; Technology adoption;	Yellow
Cluster 5 (4 items)	Financial advice; Household finance; Portfolio management; Robo-advisor	Purple

Systematic Literature Review

The VOSViewer software shows the network mapping, clustering, and explanation of the keyword connection. Furthermore, every objective research has a specific method to verify, explore, or define the research field. The research method in the financial robo-advisor can vary depending on the researcher's objective and creativity. Figure 9 showcases the literature mapping of financial robo-advisor, while every objective's detail is explained in Table 2.

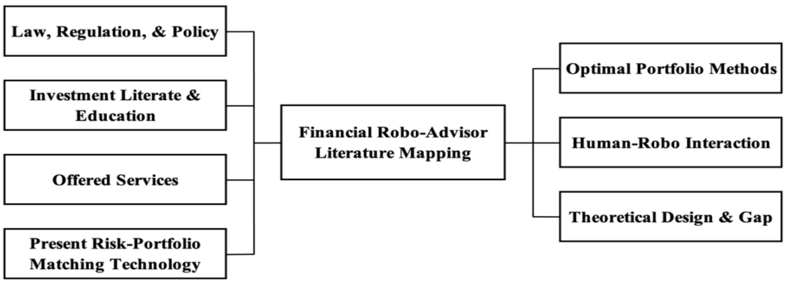

Figure 9. Financial Robo-Advisor Literature Mapping

Table 2. The Financial Robo-Advisor Mapping

Cluster Themes	Number of Articles
Law, Regulation, and Policy	8
Investment Literate and Education	4
Offered Service	15
Present Risk-Portfolio Matching Technology	6
Optimal Portfolio Methods	37
Human-Robo Interaction	17
Theoretical & Conceptual Framework	18

Law, Regulation, and Policy

Regulation, policy, and law are the emerging issues in the financial robo-advisor. In table 3, researchers mainly propose a comprehensive understanding based on financial robo-advisor applications and how robo-advisor will affect the technology functionality in human well-being.

Table 3. Law, Regulation, and Policy

Author(s)	Method(s)
Bayón (2018)	Examination
Brummer and Yadav (2019)	Explanation
Garvía (2018)	Examination
Guo (2020)	Recommendation
Lee (2020)	Description & Exploration
Lee (2018)	Description & Explanation
Lightbourne (2017)	Examination & Exploration
Liu (2018)	Explanation

Some scholars like Lightbourne (2017) and Guo (2020) place their focus on regulating Artificial Intelligence implementation. Lightbourne (2017) uses technical and literature analysis and proposes possible alternative liability to set up a suitable liability scheme. Furthermore, Guo (2020) recommends the power of attorney and the investor's information authority in China by revising the regulation about the underlying algorithms of robo-advisor and adopting the regulatory sandbox approach.

Other scholars like Lee (2020) and Brummer and Yadav (2019) suggest the design and framework of Financial Robo-Advisor regulations. Lee (2020) considers the legal status and liability, financial I.T., security, and privacy in the A.I. implementation. In Brummer and Yadav's (2019) study, The Trilemma Model gave a hypothesis about the financial robo-advisor as the impact of Fintech growth where financial innovation will affect the market integrity, simplicity, and vice versa as in figure 10. Lee et al. (2018) emphasise the established framework for security and investor protection measures of the financial robo-advisory system. Furthermore, Garvia (2013) examines the basic regulation and relationship between the robo-advisory participant's liability, such as the programmer, owner, user, and investors.

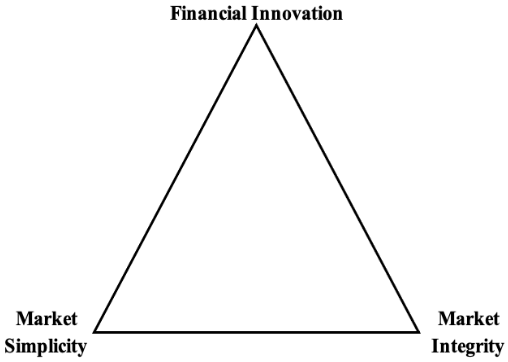

Figure 10. The Trilemma Model
Source: Brummer & Yadav (2019)

Investment Literacy and Education

The discussion about the financial robo-advisor in the context of literacy and education was also discussed. Litterscheidt and Streich (2020), Tan (2020), Xue et al. (2021), and Karkkainen et al. (2018) discuss financial literacy using a comprehensive perspective, experimental study, and quantitative method in as detailed in table 4.

Table 4. Investment Literate and Education

Author(s)	**Method(s)**
Karkkainen et al. (2018)	Examination
Litterscheidt and Streich (2020)	Ordinary Least Squares (OLS)
Tan (2020)	Exploration & Review
Xue et al. (2020)	Bootstrap Technique

Tan (2020) and Karkkainen et al. (2018) use the same method to explain, explore, and review the comprehensive understanding of the financial robo-advisor. Furthermore, Tan (2020) reviews some financial robo-advisor to get another perspective by the experience in Singapore. However, Karkkainen et al. (2018) and Litterscheidt and Streich (2020) study financial education from another perspective. Karkkainen et al. (2018) explore financial education from the curriculum perspective, and there is a need to update the economic and educational curriculum, especially with the changing technology. Otherwise, Litterscheidt and Streich (2020) use experimental study and Ordinary Leased Square (OLS) to explore how financial educatison can increase investment, especially using financial tecshnology.

Offered Service

The discussion about service is one of the popular topics in the financial robo-advisor. The published papers mainly discuss the service based on the application and expert point of view to get a deep disclosure of the financial robo-advisor implementation as in table 5.

Table 5. Offered Service

Author(s)	Method(s)
Agarwal and Chua (2020)	Review
Au et al. (2021)	Logistic Regression Analysis
Bhatia et al. (2020)	Semi-structured Interview
Brenner and Meyll (2020)	Linear Probability Model Regressions (LPM)
Bruckes et al. (2019)	Partial Lease Squares Structural Equation Modelling (PLS-SEM)
Buchanan and Wright (2021)	Review
D'Hondt et al. (2020)	Bootstrap Techniques
Gerlach & Lutz (2021)	Partial Lease Squares Structural Equation Modelling (PLS-SEM)
Godwin (2017)	Comparing Study & Digital Disclosure
Horn and Oehler (2020)	Statistical
Kabulova and Stankevičienė (2020)	Model Combination
Liu (2020)	Exploration
Tokic (2018)	Explanation & Review
Torno & Schildmann (2020)	Statistical
Tubadji et al. (2021)	Ordinary Least Square (OLS) & Regression Analysis

An exciting study developed by Bhatia et al. (2020) used the semi-structured interview to explore the deep understanding of the robo-advisor's potential from 34 experts such as bankers, I.T. experts, and fintech associations in India. They conclude that many risks present a concern in the robo-advisor, such as risk profiling model, risk tolerance, and risk analysis. They will affect wealth management firms and investors. Consequently, the government should take the initiative to educate automated wealth management investors.

Present Risk-Portfolio Matching Technology

In the risk-profiling matching technology, some researchers suggest a new recommender system and compare it with the previous method, as in table 6.

Table 6. Risk-Portfolio Matching Technology

Author(s)	Method(s)
Guidici et al. (2020)	Markowitz Model Modification
Leow (2021)	Sentiment All-Weather (SAW) & Sentiment Modern Portfolio Theory (SMPT)
Wang et al. (2019)	Gated Neural Network Structure
Xue et al. (2018a)	Incremental Multiple Kernel Extreme Learning Machine (IMK-ELM) Model
Xue et al. (2018b)	Clustering and Recommendation (CLURE) Model
Xue et al. (2018c)	Collaborative Filtering (C.F.) Algorithm & (Financial) Social Network Analysis

Xue et al. (2018a) propose IMK-ELM (Incremental Multiple Kernel-Extreme Learning Machine) to represent investor preference. It also solves a wide range of classification problems and offers an efficient deal of large-scale tasks like robo-advisor. In practice, they use a training database and calibrate it with the classification task using weighted information sources.

Furthermore, Wang et al. (2019) implemented multi-object RankNet and a gated neural network to propose stock recommendations using rank and model interaction on the financial product. The implementation of this recommender system shows that a gated neural network effectively controls the weight of RankNet in the stock recommendation.

Xue et al. (2018b;2018c) study the recommender system involving the relationship between the group and their user by proposing CLURE (CLUstering and REcommendation). This recommender has been tested by comparing Financial Social Network (FSN) to other models such as KNN (K-Nearest Neighbor), DLGB (Deep Leaning Group-Based), and Social Network-based Recommender System (SNRS). They find that FSN using a collaborative filtering algorithm can provide a valuable suggestion for group recommendations, especially for robo-advisor.

Optimal Portfolio Methods

The discussion of robo-advisor in the optimal portfolio method is divided into proposing a model, mapping, and system architecture. These articles are mapped in the Venn diagram, shown in figure 11.

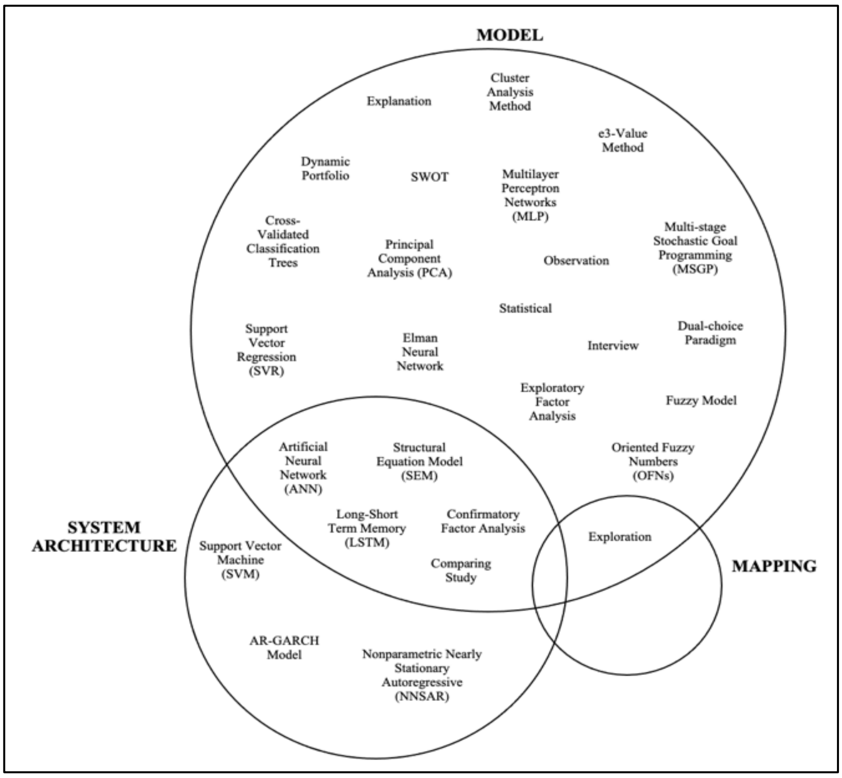

Figure 11. Diagram Venn of Model, Mapping & System Architecture in the Financial Robo-Advisor Literature

Previous researchers conducted some frameworks to build the financial robo-advisor. Day et al. (2018) used the algorithm to allocate funds to an asset, rebalance the portfolio, and suggest investment performance by preparing a report for investors. They generate a portfolio optimisation module using the modular system and integrate big data analysis, a deep learning method focusing on Long Short-Term Memory, and the Black-Litterman model. Finally, they calculate the portfolio's optimal weight the portfolio by taking the information from various sources and then developing the portfolio optimisation module. This proceeding paper is completed by step-by-step system architecture and the Black-Litterman Model.

Table 7. Optimal Portfolio Methods

Author(s)	**Method(s)**
Ahn et al. (2020)	Nonparametric nearly Stationary Autoregressive (NNSAR)
Baek et al. (2020)	Support Vector Machine (SVM) & Principal Component Analysis (PCA)
Bataev et al. (2020)	Total Cost of Ownership (TCO) Method
Belanche et al. (2019)	Confirmatory Factor Analysis (CFA) & Structural Equation Model (SEM)
Bi et al. (2020)	Long-Short Term Memory (LSTM)
Chen et al. (2021)	Principal Component Analysis (PCA) & Gaussian Mixture Model (GMM)
Cheng (2020)	Structural Equation Model (SEM)
Dai (2021)	Cluster Analysis Method
Das et al. (2020)	Goals-Based Wealth Management (GBWS)
Day and Lin (2019)	Comparing Many Model
Day et al. (2018a)	Long-Short Term Memory (LSTM)
Day et al. (2018b)	Long-Short Term Memory (LSTM)
Flavián et al. (2021)	Partial Lease Squares Structural Equation Modelling (PLS-SEM)
Gomber et al. (2018)	Exploration
Haberly et al. (2019)	Global Financial Network (GFN)
Jiang (2021)	Least Absolute Shrinkage and Selection Operator (LASSO)
Jung & Weinhardt (2018)	Ordinary Least Square (OLS) & One-way Analyses of Variance (ANOVAs)
Jung et al. (2018b)	Dual-Choice Paradigm
Kim et al. (2019)	Multi-stage Stochastic Goal Programming (MSGP)
Kobets et al. (2020)	Mathematical Model & SWOT
Kobets et al. (2018)	Mathematical Model & SWOT
Li and Chen (2019)	Support Vector Regression (SVR)
Łyczkowska-Hanćkowiak (2020)	Oriented Fuzzy Numbers (OFNs)
Méndez-Suárez et al. (2019)	Elman Neural Network & Multilayer Perceptron Networks (MLP)
Misina & Latvia (2019)	Observation
North (2020)	Fuzzy Logic
Potdar and Pande (2020)	Comparing Various Forecasting Algorithms

Author(s)	Method(s)
Riasanow et al. (2018)	Interview & e3-Value Method
Sa et al. (2018)	Exploratory Factor Analysis & Confirmatory Factor Analysis
Seiler & Fanenbruck (2021)	Partial Lease Squares (PLS)
Snihovyi et al. (2018)	Long-Short Term Memory (LSTM) & Extract-Transform-Load (ETL) Module
Snihovyi et al. (2019)	Long-Short Term Memory (LSTM) & Extract-Transform-Load (ETL) Module
So (2021)	Content Analysis
Tao et al. (2021)	Comparing Performance Using Statistical
Tyukhova & Sizykh (2019)	Cluster Analysis Method
Waliszewski & Warchlewska (2020)	Statistical
Xiang et al. (2019)	AR-GARCH Model & Smart Wealth Management Platform (SWMP)

Additionally, Day et al. (2018) developed the system architecture of the conversational system by using artificial intelligence to forecast the rise and fall of investment trust funds and generate a suitable portfolio using asset allocation. They firstly, separate the system architecture of A.I. conversational robo-advisor into two systems consisting of asset allocation and dialogue system. In the asset allocation, they then, use the Black-Litterman and Markowitz model to build the prediction trend of ETFs in Taiwan and find that the Black-Litterman model performs better than the Markowitz model in calculating the cumulative returns. The dialogue system uses the AIML (Artificial Intelligence Markup Language) to construct the conversational model, analyse the investor's risk attributes, and suggest a customised portfolio.

Human-Robo Interaction

The financial robo-advisor also talks about how the "robo" can interact with the human as well as the following effect. Some researchers, such as Ivanov et al. (2018), Mehrotra (2019), Sabharwal and Anjum (2018), and Salo and Haapio (2017), use exploration and review from other financial advisor services. Meanwhile, other researchers use quantitative and qualitative methods to shed light on the human-robo interaction in financial robo-advisor assistance shown in table 8.

The human-robo interaction in the financial robo interaction emphasises how personal touch can affect the customisation of the financial service to fulfil customer satisfaction. Some researchers, such as Ivanov et al. (2018) and Sabharwal and Anjum (2018), also reviewed some financial robo-advisor in the U.S. to explore the services such as Betterment, Charles Schwab Intelligent Portfolio or FutureAdvisor to name a few.

Another study uses experimental research to investigate anthropomorphism and analyse the investor judgments of robo-advisor in human behaviour (Adam et al., 2020; Hodge et al., 2021). In the anthropomorphism study, Adam et al. (2020) show that the human characteristics in the robo-advisor will affect the investment volumes as higher as usage intentions. Furthermore, Hodge et al. (2021) show that the advisor interaction will affect the investor's judgment, where adverse reaction will dominate over positive response, especially in humanising technology. In addition, Hildebrand and Bergner (2021) show that conversation in the robo-advisor will increase trust in using the robo-advisor, which also affects recommendation acceptance and asset allocation.

Table 8. Human-Robo Interaction

Author(s)	**Method(s)**
Adam et al. (2020)	One-way Analyses of Variance (ANOVAs)
Atwal and Bryson (2021)	Exploration
Beltramini (2018)	Interview
Bhatia et al. (2021b)	Structural Equation Model (SEM)
Brunen and Laubach(2021)	Multivariate Analysis
Deo & Sontakke (2021)	Opinion and Perception Analysis & Support Vector Machine (SVM)
Hildebrand and Bergner (2020)	Two-way Analyses of Variance (ANOVAs)
Hodge et al. (2020)	2×2 between-participants Experiment Design
Ivanov et al. (2018)	Markowitz Model of Concept Proof
Lewis (2018a)	Statistical
Lewis (2018b)	Statistical
Lourenço et al. (2020)	Structural Equation Model (SEM)
Mehrotra (2019)	Examination
Oehler et al. (2021)	Multivariate Analysis
Sabharwal & Anjum (2018)	Exploration & Review
Salo & Haapio (2017)	Exploration
Zhang et al. (2021)	Experimental Study

Theoretical & Conceptual Framework

The analysis compiles the theoretical and conceptual trajectories of robo-advisor systematic literature, as in table 9. Shanmuganathan (2020) raises the behavioural finance in the financial robo-advisor by using longitudinal studies highlighting the implementation and implication of artificial intelligence in the financial robo-advisor application. His reviews of some robo-advisor applications in the U.S. propose a comprehensive understanding of robo-advisor based on behavioural analysis. He also conducts the basic theoretical framework from the existing financial robo-advisor based on the learning model. He describes that a financial robo-advisor combines quantitative and qualitative input to explore the suitable asset allocation by using an algorithm to propose the investment suggestion that can encourage the client's investment decision—Figure 12.

Table 9. Theoretical & Conceptual Framework

Author(s)	Method(s)
Bhatia et al. (2021a)	Focus Group Discussion (FGD)
Boreiko and Massarotti (2020)	Ordinary Least Square (OLS)
Brandl and Hornuf (2020)	(Financial) Social Network Analysis
Darskuviene & Lisauskiene (2021)	Literature Review Analysis
Deng et al. (2021)	Regression
Deo & Sontakke (2021)	Experimental Study
Fan & Chatterjee (2020)	Multivariate Analysis
Giudici (2018)	Recommendation
Jung et al. (2018a)	Conceptual Study
Lu et al. (2021)	Exploration & Observation
Mehrotra & Menon (2021)	Exploration
Park et al. (2017)	Review
Paul & Sadath (2021)	Exploration
Rasiwala & Kohli (2021)	Semi-structured Interview
Ruishi & Shujun (2020)	Recommendation
Shanmuganathan (2020)	Longitudinal Case Study
Turner & Klein (2021)	Experimental Study
Wexler & Oberlander (2020)	Exploration

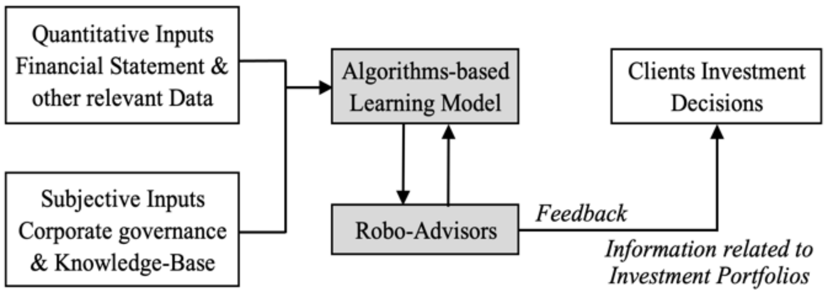

Figure 12. Theoretical Framework of Financial Robo-Advisor
Source: Shanmuganathan (2020)

Furthermore, he also defines two critical assumptions in his theoretical framework. First, the framework only focuses on investment decisions and no risks or returns associated with those investments. Second, there are differences between subjective input and quantitative inputs. Therefore, it can be concluded that personal information is still quantitative.

Otherwise, Jung et al. (2018) introduce a robo-advisor based on I.S. researchers' perspective and propose the three-phase approach of traditional human advisory, which consists of 1) Configuration, 2) Matching and Customisation, and 3) Maintenance. The phase consists of a sub-phase, which allows the customer to be directly involved in the robo-advisor service. Fan and Chatterjee (2020) also examine the utilisation of a robo-advisor based on an information search framework and innovation of the advisor's adoption. They find that a robo-advisor is preferable for people under 65 with higher risk tolerance and investment knowledge. These findings imply that the segmented use of a recent technology requires further considerations in marketing and other benefits.

FURTHER STUDY

Financial Robo-Advisor is one of the recent contributions of technology to increase investment literacy to many people. It integrates the financial technology, portfolio management, and personal characteristic of the investors to encourage the investment decision. It was different with robo-trading, especially in asset allocation. The study aims to explore financial robo-advisor based on bibliometric analysis using the mapping of VOSviewer. It explores the systematic literature analysis, which divides into (1) Law, Regulation, and Policy; (2) Investment Literate and Education; (3) Offered Services; (4) Present Risk-Portfolio Matching Technology; (5) Optimal Portfolio Methods; (6) Human-Robo Interaction; (7) Theoretical Design and Gap. In general, the method used by previous studies consists of machine learning, comprehensive understanding, and quantitative and qualitative methods.

This study is limited by the resources of literature analysis, which were only based on the Scopus collections from 2017-2021, consisting of 125 articles and conference papers. Hence, only 105 research were used for literature analysis. The following research can add more resources to determine the bibliometric analysis and explore systematic literature analysis. They can be compared to the global trends of robo-advisor in emerging markets or developed countries. The differences in law and regulation may offer extended conversation to this recent topic.

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