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A Systematic Review on Robo-Advisors in Fintech

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Abstract

Technology has been the main driver for the financial sector. Fintech tools emerged to support the provision of financial services, especially Robo-Advisors (RAs), which allow the automation of the investment management process. The main functions are the creation of an investment portfolio and allocating assets, and daily management of investment portfolios based on a machine learning algorithm. This paper presents a literature review to summarise the importance of RAs in the financial sectors as well as the perception of investors. Also, this literature review presents the main algorithm's characteristics behind the intelligence of RAs and the primary concerns. The Scopus and Web of Science databases revealed 114 research papers. It was found that investor acceptance of these technologies is affected by aspects of high volatility, which includes financial markets. The algorithm's mathematical models and system architecture might be improved so that this instrument can better suit the needs of investors.

Keywords: Machine Learning; FinTech; Robo-Advisor; Algorithm; Artificial Intelligence.

1. INTRODUCTION

This paper summarises a systematic literature review of the role of Robo-Advisors (RAs) in the financial sector as well as investor acceptance of this instrument and how the algorithm underlying it might be improved.

The main concern of today's banking sector companies is to serve an increasing number of clients while ensuring high levels of efficiency and quality. The relevance of technology emerged from the endless benefits and solutions they provide to many business sectors worldwide. In the banking sector, a new branch of technology, namely FinTech, arose to benefit the financial markets, and it originated from the innovations of the Internet, blockchain, big data, 5G, cloud and edge computing, and artificial intelligence (AI) (Mei, 2022; Ashofteh & Bravo, 2019). Hereby, many FinTech tools enable the creation and efficiency of financial services in the banking sector.

Considering this, one of the applications of AI regarding FinTech is the development of RAs that advise investors about the optimum way for a portfolio allocation via automated predictive algorithms based on the profile of each investor (aversion to risk, personal income, profile investor, expectations, etc.) (Boreiko & Massarotti, 2020). Humans are emotional beings subject to fears and

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hopes that affect their decision-making. For that reason, investors are more satisfied with Machine Learning (ML) based on facts and concrete data (Lopez de Prado, 2018). Furthermore, making this tool available means providing a low-cost service more attractive to lower-income individuals and a more significant investment efficiency with 24/7 access (Oehler, Horn, & Wendt, 2021). However, this tool is based on an algorithm, and it is possible that can exist a barrier to its operation when having to deal with random processes (stochastic) since even if investment decisions are made based on market trends, this may not be able to make perfect investment decisions (Filiz, Judek, Lorenz, & Spiwoks, 2022).

Considering the different ways of thinking of human beings, which may differ depending on the social environment in which they live, it aims to include the research works in English and Portuguese languages to study algorithms underlying this tool that may better adapt to the demands of investors. In fact, by understanding the flaws of the algorithm and adapting it to the needs of investors by transforming the disadvantages into advantages and enhancing the existing advantages, it is intended to evaluate the possibility of extending the acquisition of this tool as a form of personal investment management and to keep up with the global growth of FinTech.

A systematic review of Web of Science and Scopus was developed and organised into different sections, namely Section 2, which presents the methods and research framework; Section 3, which presents the results: the content analysis is covered in Section 4; Section 5 contains some concluding remarks; and finally, Section 6 describes the main research gaps.

2. MATERIAL AND METHODS

2.1 RESEARCH FRAMEWORK

The literature review was conducted based on the following research framework to structure and support the literature data (see Figure 1).

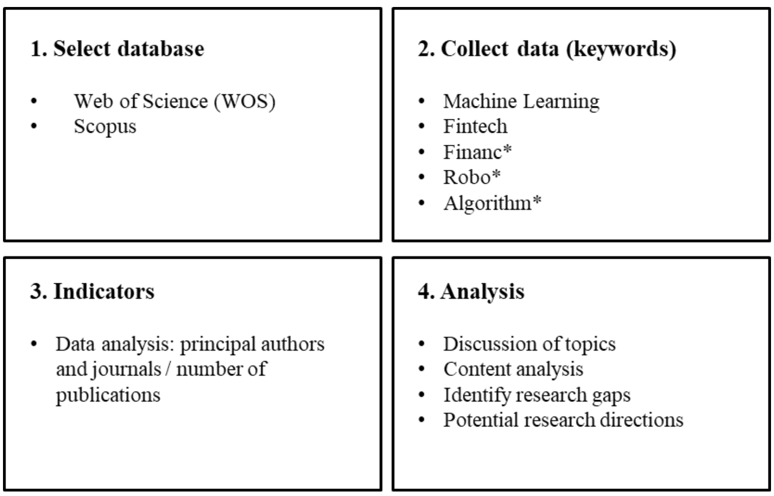

Figure 1 – Research framework

Source: Author's preparation. Content based on Templier, Mathieu and Paré, Guy, 2015

The literature data used in this review were obtained through academic databases, namely Web of Science (WOS) and Scopus.

To extract information from the respective databases, a search algorithm was selected, with different keywords considered relevant to the approach of the topic under analysis (("Machine Learning" OR "Fintech" OR "Artificial Intelligence") AND "Financ*" AND ("Invest*" OR "Risk*") AND "Robo*" AND "Advis*" AND ("Algorithm*" OR "Cod*")).

The results obtained were filtered in time, selecting only the results between 2019 and 2023, considering the more recent results regarding new areas of study and other topics that might be the subject of discussion nowadays, enabling the literature data to be more relevant and current. Thus, 679 results were obtained by combining keywords and year filters in the selected databases (WOS and Scopus). To deal with a high amount of information obtained, Mendeley was another tool selected for filtering the information, eliminating duplicate results that may exist in previously obtained results.

From this step, it is crucial to understand the relevance of specific results by reading and analysing the abstracts and applying filters that exclude results that refer to a subject that does not coincide with the one under analysis (Medicine, Education, etc.). At this stage, it is important to detail the criteria applied for the exclusion of articles according to the criterion of irrelevant study area, considering as such the following study areas: medicine, psychology, nursing, energy, earth, arts and humanities, health, chemistry, pharmacy, mathematics, biology, engineering and agriculture. On the other hand, a filter was adopted to identify keywords of the selected articles, and articles containing the keywords "agriculture", "*aged care*", "*convolution*", "*vehicles*", "*students*", "*cultural institutions*", "*city of london*", "*civil-military relations*", "*civil rights and obligations*", "*color space transformation*" and other related keywords were excluded. Through this filtering it was possible to exclude about 400 articles considered irrelevant to the study in question and that do not address robo-advisors as the main topic.

Furthermore, to ensure that the results also presented Portuguese research works, we considered research works in Portuguese and English for our analysis. Also, results that refer to books and book chapters were excluded since, at this stage, we intend to select and analyse research about the subject.

Before starting the systematic literature review, a backward citation search was carried out on several documents based on different combinations of keywords and filters, obtaining other relevant documents that should be part of the literature data. In addition, articles corresponding to the current year 2023 were identified through a critical analysis, since the articles published this year are extremely important because the topics addressed are more recent and considered the "hot topics" of the discussion. As mentioned, as result of a manual critical review 6 articles were considered for this study with the focus on RAs, and on the other hand, address topics that can actually add value to the research.

2.2 RELATED WORKS

The identification of related works is fundamental by allowing a more extended insight into the existing literature in this area of study and the recent contributions regarding RAs in general, also serving as a basis for this study ensuring the most recent and relevant topics, as well as a fundamental understanding of the topic and the research area itself. In a development stage of the study, through the identification of related works it may be possible to ensure and reinforce the need for the research topic by identifying limitations in other studies, or even comparing conclusions already made to ensure the validity of the study under analysis. Also, having as a basis a single source of information does not provide confidence about the study being presented, it becomes necessary to identify different sources of information.

Through an analysis based on the keywords selected and filters applied, 27 reviews were identified. These were manually analyzed, and 8 reviews were selected that could be considered as related works because they have very similar objectives and, above all, have gaps that this research seeks to address, being works that complement each other and, at the same time, make a great contribution to the subject under analysis.

Author	Year	Title
Cannavacciuolo et al.	2023	*Technological Innovation-Enabling Industry 4.0 Paradigm: A systematic literature review*
Semko	2019	*Machine learning for robo-advisors: testing for neurons specialization*
Quiroga-Garcia, Arenas-Parra, & Rico-Pérez	2022	*Scientific Development of Robo-Advisor: A Bibliometric Analysis*
Ahmed, Alshater, Ammari, & Hammami,	2022	*Artificial intelligence and machine learning in finance: A bibliometric review*
Loureiro, Guerreiro, & Tussyadiah,	2021	*Artificial intelligence in business: State of the art and future research agenda*
Mahmud, Islam, Ahmed, & Smolander,	2022	*What influences algorithmic decision-making? A systematic literature review on algorithm aversion*
Elia, Stefanelli, & Ferilli,	2022	*Investigating the role of Fintech in the banking industry: what do we know?*
Omarova	2019	*New tech v. new deal: fintech as a systemic phenomenon*

The main objectives of the identified related works concern the growth and environment of RAs in investment services, highlighting the importance of financial technology innovation for the development of financial services provision referencing Industry 4.0, which has significantly contributed to the development of RAs (Cannavacciuolo et al., 2023). The remaining related works, on the other hand, focus on fintech topics, which includes the RA tool and its impact on the banking industry (Elia, et. al., 2022), followed by other works that aim to understand how mature AR research is at the moment (Quiroga-Garcia, et al., 2022). On the other hand, works related to ML and AI where we intend to evaluate and analyze which tools combine these two themes in the area of finance and which can support a decision process, are also presented (Ahmed, et al, 2022.), as well as ML methodologies with neurons with RAs (Semko, 2019). In this sense, some related works also present points that influence algorithm aversion by presenting open themes and topics (Mahmud, et al, 2022). Another of the related works presents an RA approach in cryptocurrency (Omarova, 2019).

3. RESULTS

Through this research, 115 results are considered relevant to the subject under analysis. The filtering process is presented in Figure 2 through the PRISMA flow diagram.

The results obtained through applied filters correspond to articles, conference papers, literature reviews, editorials, and short surveys. Articles represent 68.42% of the results, which means 78 results, followed by review papers with 23%, approximately.

Type of document	Number of results	%
Article	78	68.42%
Review	26	22.80%
Conference Paper	9	7.89%
Editorial	1	0.88%
Total	**114**	**100%**

Table 1 – Number of results by type of document

In 2022 there was a more significant number of publications, namely 47, followed by 2021 with 24. Regarding the number of citations in 2021, 912 were identified; in 2022, there were 398 citations.

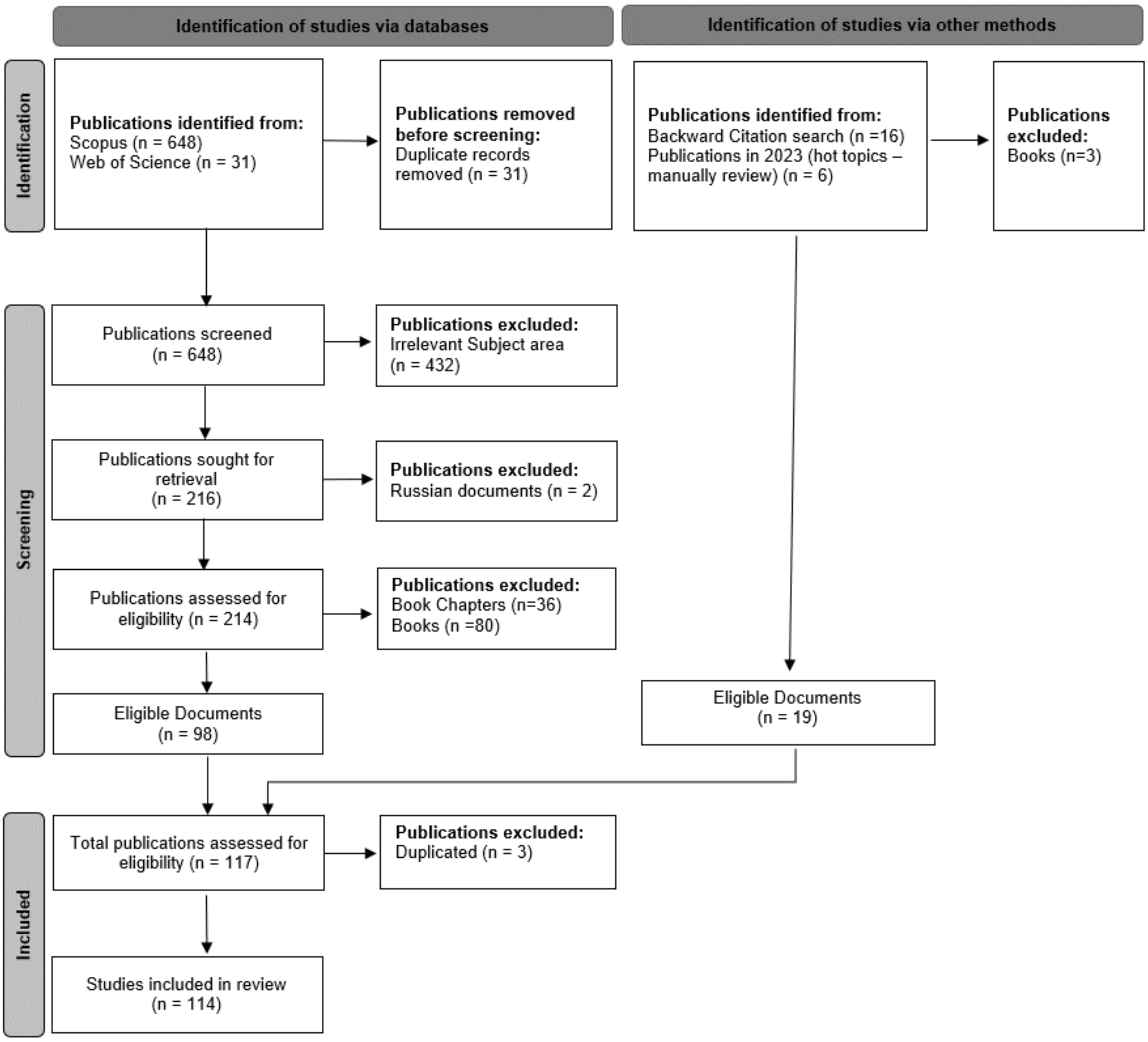

Figure 2 – Literature review - PRISMA flow diagram.
Source: Page MJ, et al., 2020

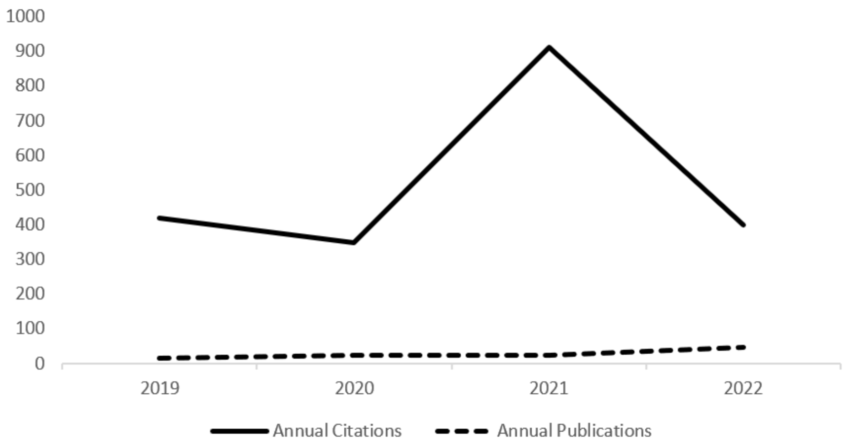

Figure 3 – Number of citations and publications by year

Regarding the source of information, the principal journals that publish about the subject are *Journal of Business Research,* which focuses on research developed for business activity. *Applied Sciences*, a scientific journal covering all aspects of applied physics, applied chemistry, applied biology and engineering, environmental and earth sciences and also *Communications in Computer and Information Science*, a journal that publishes about computer science and mathematics. The top 5 journals with publications about the subject under analysis are presented below in Figure 4.

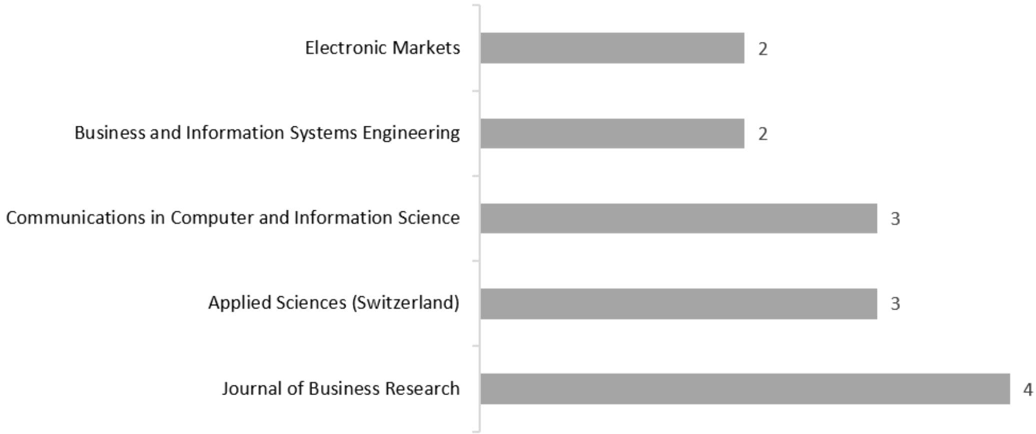

Figure 4 – Top 5 journals and the respective number of publications

The VOS Viewer tool was also adopted to analyze the fundamental characteristics of publications about the subject under analysis, which allows the visualization of bibliometric networks as shown in Figure 5.

According to the analysis of Figure 5, it is possible to identify a main author, namely Vitaliy Kobets and Oliver Hinz, with 5 and 3 articles published, respectively, followed by six authors with 2 articles published, namely Stefan Morana, Khalid Khan, Muneer Maher Alshater, Jihoon Lee, Valeria Yatsenko and Serhii Savchenko (Appendix 1).

Additionally, a keyword analysis was carried out using the VOS Viewer, analyzing the co-occurrence of author keywords with the complete counting method. The keywords were extracted from the title and abstract fields of the 115 articles, ignored by structured abstract labels and copyright statements. For the keyword analysis, the keywords with at least 10 occurrences were selected, and a relevance score was automatically calculated for selecting the 60% most relevant terms, which resulted in 46 keywords. Through this analysis, it is possible to visualise the most used keywords presented in Figure 6.

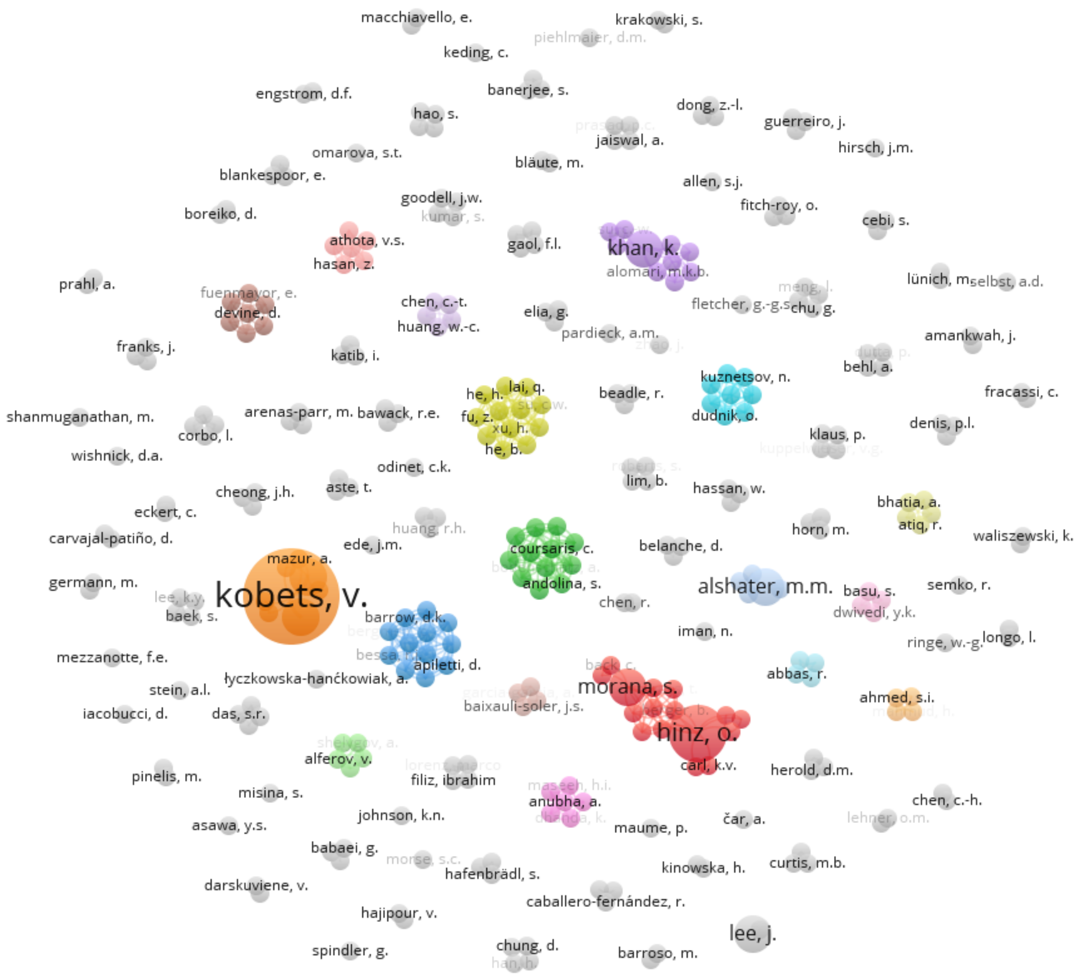

Figure 5 – Visualization analysis of the main authors (based on number of publications)

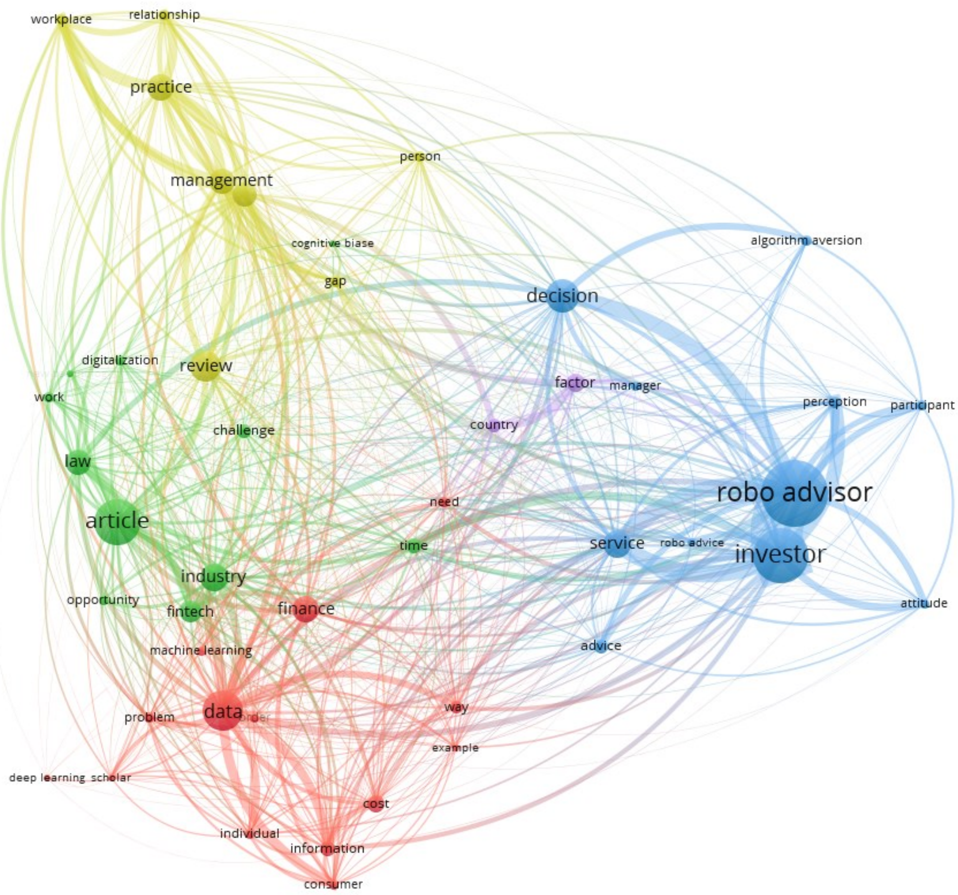

Figure 6 – Keywords

Through Figure 6, it is possible to verify that the most used keywords are "*robo advisor*", "*investor*", "*article*" "*decision*", and "*data*", which mostly corresponds to the keywords adopted in the first steps.

After a detailed analysis of the articles, 38 articles were excluded because, despite all the filters applied, they presented studies in the hospitality, energy and health industries, which do not correspond to what is studied in this article.

In this sense, 76 articles were considered, including 27 literature reviews as related works (chapter 2.2), 6 conference papers and 43 articles relevant to the topic in question that are organized by different topics as shown in table 2.

Topic	Authors	Title	Journal / Conference
Relationship between RAs and investor	Belanche, D., Casaló, L.V. and Flavián, C. (2019)	*Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers*	Industrial Management & Data Systems
	Ozmen Garibay O.; Winslow B.; Andolina S.; Antona M.; Bodenschatz A.; Coursaris C.; Falco G.; Fiore S.M.; Garibay I.; Grieman K.; Havens J.C.; Jirotka M.; Kacorri H.; Karwowski W.; Kider J.; Konstan J.; Koon S.; Lopez-Gonzalez M.; Maifeld-Carucci I.; McGregor S.; Salvendy G.; Shneiderman B.; Stephanidis C.; Strobel C.; Ten Holter C.; Xu W. (2023)	*Six Human-Centered Artificial Intelligence Grand Challenges*	International Journal of Human-Computer Interaction
	Chung D.; Jeong P.; Kwon D.; Han H. (2023)	*Technology acceptance prediction of robo-advisors by machine learning*	Intelligent Systems with Applications
	Back C.; Morana S.; Spann M. (2023)	*When do robo-advisors make us better investors? The impact of social design elements on investor behavior*	Journal of Behavioral and Experimental Economics
	Athota V.S.; Pereira V.; Hasan Z.; Vaz D.; Laker B.; Reppas D. (2023)	*Overcoming financial planners' cognitive biases through digitalization: A qualitative study*	Journal of Business Research
	Boreiko, D., & Massarotti, F. (2020)	*How Risk Profiles of Investors Affect Robo-Advised Portfolios*	Frontiers In Artificial Intelligence
	Chua, A.Y.K., Pal, A. and Banerjee, S. (2023)	*AI-enabled investment advice Will users buy it*	Computers in Human Behaviour
	Germann, M., & Merkle, C. (2022)	*Algorithm aversion in delegated investing*	Journal of Business Economics
	Heßler, P. O., Pfeiffer, J., & Hafenbrädl, S. (2022)	*When self-humanization leads to algorithm aversion*	Business & Information Systems Engineering
	Johnson, K. N. (2019)	*Automating the risk of bias*	George Washington Law Review
	Kobets, V., Yatsenko, V. and Voynarenko, M. (2020)	*Cluster Analysis of Countries Inequality Due to IT Development Through Macros Application*	Information and Communication Technologies in Education, Research, and Industrial Applications / 15th International Conference on Information and Communication Technologies in Education,

Topic	Authors	Title	Journal / Conference
			Research, and Industrial Applications, ICTERI
	Lu, B., Hao, S., Pinedo, M., & Xu, Y. (2021)	*Frontiers in service science: Fintech operations—An overview of recent developments and future research directions*	Service Science
	Maedche, A. et al. (2019)	*AI-Based Digital Assistants: Opportunities, Threats, and Research Perspectives*	Business & Information Systems Engineering
	Piehlmaier, D. M. (2022)	*Overconfidence and the adoption of robo-advice: Why overconfident investors drive the expansion of automated financial advice*	Financial Innovation
	Prahl, A., & Van Swol, L. (2021)	*Out with the humans, in with the machines?: Investigating the behavioral and psychological effects of replacing human advisors with a machine*	Human-Machine Communication
	Shanmuganathan, M. (2020)	*Behavioural finance in an era of artificial intelligence: Longitudinal case study of robo-advisors in investment decisions*	Journal of Behavioral and Experimental Finance
	Oehler, A., Horn, M., & Wendt, S. (2021)	*Investor Characteristics and their Impact on the Decision to use a Robo-advisor*	Journal Of Financial Services Research
	Zacharias, J. et al. (2022)	*Designing a feature selection method based on explainable artificial intelligence*	Electronic Markets
	Zhao J. (2022)	*Artificial intelligence and corporate decisions: fantasy, reality or destiny*	Catholic University Law Review
Characteristics of the algorithm/model of RAs	Alferov, V., Vysotskaya, N., Vernikov, V., Shelygov, A., & Stepanova, D. (2022)	*Opportunities of digital financial advice platforms for private investors: a qualitative case study of European and 170uropean companies' practices*	Relações Internacionais no Mundo Atual
	Asawa, Y. S. (2022)	*Modern machine learning solutions for portfolio selection*	IEEE Engineering Management Review
	Huang W.-C.; Chen C.-T.; Lee C.; Kuo F.-H.; Huang S.-H. (2023)	*Attentive gated graph sequence neural network-based time-series information fusion for financial trading*	Information Fusion
	Babaei, G., & Giudici, P. (2021)	*Explainable artificial intelligence for crypto asset allocation*	SSRN Electronic Journal

Topic	Authors	Title	Journal / Conference
	Baek, S., Lee, K. Y., Uctum, M., & Oh, S. H. (2020)	*Robo-advisors: Machine learning in trend-following ETF investments*	Sustainability (Switzerland)
	Carvajal-Patiño, D., & Ramos-Pollán, R. (2022)	*Synthetic data generation with deep generative models to enhance predictive tasks in trading strategies*	Research in International Business and Finance
	Das, S. R., Ostrov, D., Radhakrishnan, A., & Srivastav, D. (2019)	*Dynamic portfolio allocation in goals-based wealth management*	Computational Management Science
	Dong, Z., Zhu, M., & Xu, F. (2021)	*Robo-advisor using closed-form solutions for investors' risk preferences*	Applied Economics Letters
	Filiz, I., Judek, J., Lorenz, M., & Spiwoks, M. (2022)	*Algorithm Aversion as an Obstacle in the Establishment of Robo Advisors*	Journal Of Risk and Financial Management
	Fletcher, G. (2021)	*Deterring Algorithmic Manipulation*	Vanderbilt Law Review
	Fracassi, C., & Magnuson, W. (2021)	*Data autonomy*	Vanderbilt Law Review
	Huang, R. H., et al. (2022)	*The development and regulation of robo-advisors in Hong Kong: Empirical and comparative perspectives*	Journal of Corporate Law Studies
	Kobets, V.M. et al. (2020)	*Data analysis of personalized investment decision making using robo-advisers*	Science and innovation
	Kobets, V., Petrov, O., & Koval, S. (2022)	*Sustainable Robo-Advisor Bot and Investment Advice-Taking Behaviour*	14th PLAIS EuroSymposium on Digital Transformation, PLAIS EuroSymposium
	Lee, J. (2020)	*Access to finance for artificial intelligence regulation in the financial services industry*	European Business Organization Law Review
	Lehner, O. M., & Simlinger, R., 2019).	*When function meets emotion, change can happen: Societal value propositions and disruptive potential in fintechs*	The International Journal of Entrepreneurship and Innovation
	Łyczkowska-Hanćkowiak, A. (2020)	*On application oriented fuzzy numbers for imprecise investment recommendations*	Symmetry
	Malibari, N., Katib, I., & Mehmood, R. (2022)	*Smart robotic strategies and advice for stock trading using deep transformer reinforcement learning*	Applied Sciences
	Misina, S. (2019)	*Financial web calculators*	60th International Scientific Conference on Information Technology and

Topic	Authors	Title	Journal / Conference
			Management Science of Riga Technical University (ITMS)
	Pinelis, M., & Ruppert, D. (2022)	*Machine learning portfolio allocation*	The Journal of Finance and Data Science
	Poh, D., Lim, B., Zohren, S., & Roberts, S. (2021)	*Building cross-sectional systematic strategies by learning to rank*	The Journal of Financial Data Science
	Savchenko, S. and Kobets, V. (2022)	*Development of Robo-Advisor System for Personalized Investment and Insurance Portfolio Generation*	Communications in Computer and Information Science / 17th International Conference on Information and Communication Technologies in Education, Research, and Industrial Applications, ICTERI
	Savchenko, S. and Kobets, V. (2022)	*Development of Software Architecture and Machine Learning Modules of Robo-Advisor System for Personalized Investment Portfolio Generation*	Information and Communication Technologies in Education, Research, and Industrial Applications / 17th International Conference on Information and Communication Technologies in Education, Research, and Industrial Applications , ICTERI
	Thießen, F., & Bläute, M. (2022)	*On the effectiveness of signaling strategies in the Field of online investing*	Credit and Capital Markets
	Tsai, S., & Chen, C. (2022)	*Exploring the innovation diffusion of big data robo-advisor*	Applied System Innovation
Type of investor and RAs in specific geographies	Alshater, M. M., & Othman, A. H. (2020)	*Financial Technology Developments and their Effect on Islamic Finance Education*	Journal of King Abdulaziz University, Islamic Economics
	Bhatia, A. et al. (2021)	*Artificial intelligence in financial services: a qualitative research to discover robo-advisory services*	Qualitative Research in Financial Markets

Topic	Authors	Title	Journal / Conference
	Prasad, P. C., Jaiswal, A., Shakya, S., & Singh, S. (2021)	*Portfolio optimization: A study of Nepal stock exchange*	International Conference on Sustainable Expert Systems, ICSES
	Song, Y., & Lee, J. (2020)	*Importance of event binary features in stock price prediction*	Applied Sciences
	Waliszewski, K., & Warchlewska, A. (2021)	*Selected countries of eastern and Central Europe in the face of challenges of modern financial technologies (on the example of robo-advice)*	Przegląd Wschodnioeuropejski

Table 2 – Articles organised by topic.

4. CONTENT ANALYSIS

The selected studies address different perspectives on RAs and are considered the most relevant for the topic under review. The articles under discussion were identified in the previous chapter, although there is also an author that refers some important topics to this research in a book (Lemma , 2020), and for that reason it was addressed to discussion as well.

In this case, many authors address the advantages and disadvantages of combining technology and humans, focusing on the financial context and a scenario that is difficult to predict.

Relationship between RA and investor

The development of the fintech sector has been constant as can be seen in an article published by Lu et. al. (2021), which focuses on financial technology and applications in different topics, in particular RAs, and research directions are identified which is interesting to consider for this research (Lu, Hao, Pinedo, & Xu, 2021).

Following the adoption of artificial intelligence technologies and how they should be applied and adapted to the human being, it is important to mention six challenges that have been studied by Ozmen Garibay, O. et al. and that should be considered by the scientific community in the development of technologies that focus on people and the human being, and also that present fundamental characteristics such as ethics, fairness, and appreciation of the human condition. The challenges identified "*(1) is centred in human wellbeing, (2) is designed responsibly, (3) respects privacy, (4) follows human-centred design principles, (5) is subject to appropriate governance and oversight, and (6) interacts with individuals while respecting human's cognitive capacities*" (Ozmen Garibay et al., 2023).

In addition, it is important to understand the advantages and disadvantages of technology for human beings. In this sense, there are numerous authors who refer to Industry 4.0 as a revolution in the way companies and people adopt technology in their business model and the countless opportunities that are created between technology and humans, where for example Kobets et. al states that this revolution "*creates new possibilities for digitization, robotics, automation of all business processes, creation of modern products"*, which can increase the level of frictional and structural unemployment, resulting in the inequality gap between different segments of the world's population (Kobets, Yatsenko, & Voynarenko, 2020).

From a financial and human-focused perspective, the truth is that technology can bring numerous benefits, particularly in the decision-making process in financial matters, where artificial intelligence can make a significant contribution (Maedche et al., 2019), and in fact people tend to accept this method in their decision-making based on the confidence and accuracy of the results. In fact, there has been an increase in recent years in the complexity of the decision-making process affecting individual wellbeing. Thus, by adopting automation methodologies through artificial intelligence, it may be advantageous for certain consumers to access low-cost financial advisory services as well as provide insights into RAs and their design characteristics (Back, Morana, & Spann, 2023).

In situations of uncertainty, the results are slightly different, verifying that *"a favorable attitude toward AI was a necessary but no longer sufficient condition for AI acceptance*" (Chua, Pal, & Banerjee, 2023). In order to contribute to a greater acceptance of AI tools, the importance of transparency is mentioned throughout the research, namely the logical reasoning about how AI systems can impact the individual decision process (Zacharias et al., 2022).

Regarding RAs, it is considered as an understudied tool, and some authors try to understand the reasons why investors adopt this tool, focusing on the causal effect of investor overconfidence on the willingness to use RAs, showing that in a pre-chasma market, overconfident investors have a significantly higher propensity to adopt robo-advice (Piehlmaier, 2022). There is a lot of RAs in the financial market and some authors identify the differences between the different RAs that can also impact the choice of the investor, namely in the type of investment plans offered, the minimum investment amounts and the service fees (Alferov, et al., 2022).

Aversion to risk

In surveys conducted by Germann (2022) some participants stated that human fund managers are better able to deal with one-off events, such as a financial crisis or a pandemic, and prefer to see algorithms as a support tool for human fund managers, rather than as a competitor, which may reduce the level of aversion to this tool among potential investors. On the other hand, it is also considered important how the tool is presented to the public and potential consumers, and it may make sense to present the tool as something programmed by humans (Germann, et. al., 2022). Therefore, from a marketing and tool advertising perspective, there are studies that have investigated the effectiveness of signaling strategies in innovative service offerings, in order to support investors in assessing the reliability and credibility of new providers and their offerings (Thießen, & Bläute, 2022). Following this topic, based on research carried out using a ML approach with the adoption of predictive models, Chung D. suggests there is a need for detailed customization of the RAs on the market and that the companies must show how much more enjoyable it is to purchase these services compared to already existing investment services. It should be noted that this study does not deny the importance of more technical components of RAs to obtain a more transparent and accurate algorithm but concludes that these are characteristics not so much relevant in the acceptance of the technology by the user (Chung et al., 2023).

Also, it could be enough to have a period of "bad luck" for investors to stop considering the tool as generating good returns, however in the experiment carried out this was not verified, and the participants do not punish algorithms more than human managers (Germann, et. al., 2022). Additionally, in a study conducted with a sample of participants, Prahl and Van Swol (2021) aimed to study the replacement of a human advisor by a machine, and it was found that the participants considered the human advisor more specialized, and there was less reciprocity and blaming for errors when a machine was involved (Prahl, et. al., 2021).

According to research conducted, Oehler et al. highlight that people who have adopted RAs in an investment context come to invest more compared to other people who are more averse to this tool and also exhibit the ability to invest more "on their own in both stocks and bonds" (Filiz et al., 2022). In this regard, it is also worth mentioning that AI can be adopted to help plan and streamline data analysis processes and provide an unbiased analysis of step-by-step solutions that financial planners can then take forward in investments plan (Athota et al., 2023).

Decision-making

Several factors can impact investors' decisions, such as cost, trust, and information security behavioural biases, among others. In the case of RAs, it is found that mass media and intrapersonal characteristics can be considered as two determinants of RAs' trust, where it is found that "*the influences of perceived usefulness and attitude are slightly higher for users with a higher level of familiarity with robots*" (Belanche et al., 2019).

When it comes to evaluating algorithmic or automated decision-making platforms, it should be considered that they may lead to more efficient, accurate and objective decisions, but on the other hand, they may demonstrate biases, going against what has been said that algorithms will democratize markets and increase inclusion. It should be noted that with the recent financial crisis, "*firms adopted structural and procedural governance reforms to mitigate various enterprise risks; these approaches may prove valuable in mitigating the risk of algorithmic bias.*" (Johnson, 2019).

The concept of self-humanization has a great influence in decision contexts, and understanding this concept better can help to understand what users want from decision support systems and how they can be designed. Additionally, "*uniquely human attributes*", a concept that distinguishes humans from animals such as cognitive abilities, logic and rationality, can also play an important role in the design of decision support systems, and can strengthen the link between humans and algorithms, since they are attributes that can be shared with machines. (Heßler, et. al., 2022)

In addition, making investment decisions is usually considered difficult for clients when they are based on risk factors, and it is often customary for them to seek advice from professionals in the field. However, a study has shown that when it comes to assessing clients seeking professional advice, many of them searched for RA services on a platform that includes access to live advisors and customizable professional advice. (Shanmuganathan, 2020).

The use of an RA is advantageous when dealing with situations where urgent decision making is required based on a large amount of data and variables. In this sense, not only Ars, but AI-based tools have a very important role in enabling more informed and higher quality decisions (Zhao, 2022).

Characteristics of the algorithm/model of RAs

The selected studies refer to the main variables of RAs, as well as the architecture of the tool and mathematical models that allow the construction of an investment portfolio based on ML techniques to forecast the returns of financial products (Ashofteh, Bravo, & Ayuso, 2021; Savchenko & Kobets, 2022).

Consumers seek an efficient balance between consumption and savings resulting in an investment solution. Currently, this is a need easily solved by adopting automated systems, namely the services of RAs that have a mathematical algorithm based on models and basic principles of consumption-savings theories (Kobets et al., 2020).

Algorithms

In this framework, some papers present new ways to implement this tool and some authors present different types of RA designs, each varying according to the respective target. Kobets et. al (2022) developed a RA that aims to choose the best financial instruments considering the risk-return criterion by adopting different investment strategies detailed throughout the article, also an experimental comparison between different methods regarding optimal investment portfolios and predictions of return on assets (Savchenko & Kobets, 2022). In this sequence, the design of an RA is also presented, in this case in a Chinese context, which presents a complex structure that allows it to analyze a large number of assets with extremely fast algorithms, adopting a dynamic weighting to the different preferences of investors, and the results obtained, based on real data from the Chinese stock market, allow us to conclude that the designed RA can accurately estimate the best portfolio of assets taking into account the risk preferences of investors (Dong, et. al., 2021).

As previously mentioned, the algorithms presented by the authors take into account different types of investors, and this time an RAs is presented that focuses on the return on investment over a designated time horizon, distinguishing itself from the others by taking into account the periodic inflow and outflow of money without degrading the performance or the predefined time horizon, this algorithm being oriented towards the investor's assets, maximum wealth and objectives (Das, S. R., et. al., 2019). It is known that one of the many disadvantages of long-term investments is the impossibility of redeeming part of that investment and, on the other hand, reinforcing it, so this algorithm presents a different perspective, capable of attracting different types of investors, namely those with a profile more averse to investment with a long-time horizon.

Poh et. al. (2021) argues that for the success of the algorithms and models, it is necessary to perform an accurate classification of assets before constructing a portfolio, and the author suggests incorporating learning algorithms to obtain an improvement in classification accuracy. Through a study conducted, it was observed that the use of modern machine learning classification algorithms results in better performance and provides higher Sharpe ratios compared to more conventional and traditional methods (Poh, Lim, Zohren, & Roberts, 2021). On the other hand, the authors Malibari, Katib and Mehmood (2022) developed an architecture through deep reinforcement learning (DRL) with data from the Saudi Arabian Stock Exchange (Tadawul). The developed architecture considered seven reward functions namely Sortino ratio, cumulative return, annual volatility, omega, Calmar ratio, maximum drawdown and normal reward without any risk adjustments. Through this architecture based on DRL, there was an increase in the equity of indices of previously selected companies, concluding that the study carried out by these authors provides very significant contributions in long-term investment (Malibari, Katib, & Mehmood, 2022).

RAs can be a very useful tool for assets such as cryptocurrencies, as they present high levels of return, but also high risks and high volatility. In this regard, Babaei, & Giudici (2021) focused on the development of a tool for this type of assets, presenting a methodology that can explain how asset choices are made by an RA that works according to Markowitz's asset allocation, and that suggest its implementation for supervisors who assess the compliance of RAs according to financial regulations and even Fintech companies that intend to make this assessment internally. The same authors propose as future research the application of different portfolio optimization methods that are more complex than Markowitz that consider systemic risk and/or tail risk (Babaei, G. et. al., 2021). In this regard, other authors report that to obtain more profitable algorithms, it should take into account the level of risk aversion of investors, dealing with two objectives that are difficult to combine, minimizing risk and maximizing return in a static and dynamic way. However, the imprecision of the data is taken into account, so RAs could be adapted through fuzzy logic by using fuzzy numbers (Łyczkowska-Hanćkowiak, 2020).

Baek, S, et. al. (2020) analyzed an ML application dedicated to investments in ETF funds traded on the US stock market, designing an algorithmic trading system with the factor model a support vector machine, whereby the trading system was found to present what is desirable in terms of robustness (Baek, S, et. al., 2020).

ML Models

Many articles analyze several models of RAs that allow you to create an optimal investment portfolio. In this sense, Asawa (2022) presents in its article a review of various ML techniques for portfolio optimization such as clustering, vector machines, genetic algorithm and many others (Asawa, 2022).

Pinelis and Ruppert (Pinelis & Ruppert, 2022) refer that "*optimal portfolio rules for time-varying expected returns and volatility are implemented with two Random Forest models*", where throughout the paper it is presented a unifying framework for ML applied to both return-and volatility-timing.

Furthermore, Huang et al. mention throughout their research that there is some difficulty in applying mathematical models in data prediction cases. Huang et al. (2023) indicate that "*by combining financial information from the financial market, we apply an information fusion approach to collect data*", further indicating that it is possible to develop a relational model through the use of deep neural network being represented through a graph structure with the goal to determining the actual market conditions. The research intends to present the "*visual-question answering-like deep learning fusion model based on the graph structure and attention mechanism*". Through the adopted method, the conclusions are based on the improvement of "*the accuracy of trend and volatility prediction up to 6% on S&P500*" and the development of "*a pairs trading application*." (Huang et al., 2023). To predict data, the authors Carvajal-Patiño and Ramos-Pollán (2022) developed an exhaustive analysis of predictive models based on synthetic data to perform better simulations (Carvajal-Patiño & Ramos-Pollán, 2022), being an article to explore in terms of the diversity of models that can be adopted to predict the financial asset market.

In a conference that took place in Riga in 2019, RAs are mentioned as a tool of great potential for the FinTech world. RAs can be based on a variety of models, with incremental learning classification algorithms suggested for better portfolio construction, as they dynamically adapt to the fluctuations of client assets. On the other hand, regression tree models are suggested to automate rebalancing strategies. From the perspective of risk assessment and tolerance of investors, the use of neural networks is mentioned (Misina, 2019). Furthermore, a study identifies Roger's innovation diffusion theory as a basis regarding the exploration and application of RAs for stock market prediction purposes, and the author concluded throughout the research that once investors are more confident and familiar with neural network-type actions, it is expected that this new AI stock market prediction model will become another indicator for future analysis (Tsai, & Chen, 2022).

Some authors analyse "*how societal VPs transcend individual functional and emotional ones for entrepreneurs*" (Lehner & Simlinger, 2019), and concluded with a conceptual model of how the former can build on the disruptive potential of fintechs and provide appropriate solutions to entrepreneurs seeking finance (Lehner & Simlinger, 2019).

Regulation

The regulation of RAs is important to reinforce financial inclusion and the use of this tool, so the solutions used should not be inferior to those available on the market and used by wealth management service providers working with wealthier investors (Lee, 2020).

As mentioned in previous chapters, one of the main causes for the low use of these tools is the lack of knowledge in financial areas that serve as a basis for informed decision making, and wealthier investors have the advantage of having the help of professional financial advisors in making investment decisions. In this sense, the regulation of this tool brings benefits in guaranteeing the continuity of the tool, the security in its use, protection of investors and market integrity, and providing more information about the tool, and on the other hand allows to rationalize KYC/CDD processes reducing compliance costs (Lee, 2020).

An important point regarding algorithms is their transparency, being identified by Fletcher (2021) the current law's inability to punish "*algorithmic manipulation incentivizes potential wrongdoers to utilize algorithms to cloak their misdeeds, exposing the markets to significant systemic harm*." (Fletcher, 2021).

Although in Hong Kong, a different reality from Portugal, the regulation on RAs is considered so that there is a balance between the protection of investors and the promotion of the tool, and the need to make more efforts to ensure compliance and enforcement of regulations, and the need to pay more attention to the increasing complexity of algorithms, was highlighted (Huang, et. al., 2022). Also, data privacy is one topic that need to be addressed, where people have increasingly found it difficult to reach simple strategies for saving and investing, and intermediation tools (RAs) are attractive in this sense, involving data sharing. However, a problem arises, where Fracassi and Magnuson states that a "*combination of market failure and regulatory ambiguity has led to a situation where data is limited, isolated and inaccessible, thus preventing individuals from using their data efficiently*." (Fracassi, & Magnuson, 2021)

Type of investor and RAs in specific geographies

There are different types of investors, with different characteristics and ways of thinking, that can be influenced according to the geographical location, in this case, the respective country of origin. In this sense, RAs can also take on different characteristics according to the target investor, which may differ according to the geographical location.

In India, human intervention is a key point from an emotional and investor contact perspective. As such, RAs are seen as a complementary service and not as a substitute for financial advisors (Bhatia et al., 2021). In the Islamic market, there is already a growth of fintech companies, where they are able to automate many of the day-to-day tasks of banks with the help of technology (Alshater, & Othman, 2020).

In Korea, there is a high interest of the population in investing in stocks, and there is a high level of research in predicting stock prices through deep learning that is dependent on the user's ability to collect all the characteristics of the training data (Song, & Lee, 2020)

Prakashet al. (2021) develops a paper that aims to use the assets of the Nepal Stock Exchange (NEPSE) to construct a portfolio and adopt mean-variance portfolio theory to be able to identify the optimal weight to be assigned to each asset in the portfolio through Monte Carlo simulation (Prasad, Jaiswal, Shakya, & Singh, 2021)

In Eastern and Central Europe, a high level of technological development in personal finance is reported, which can be explained by the high concentration of assets and an increasing number of users of RAs (Waliszewski, & Warchlewska, 2021). Furthermore, it should be noted that RAs, as a financial tool, are subject to legal and economic regulations within the FinTech framework in Europe, US and UK, which should be a factor to be considered when exploring new challenges in this area (Lemma, 2020).

5. CONCLUSION

The tools available on the market for portfolio personalization, namely RAs, are now standard. However, not everyone trusts these tools enough to invest their money. There are still some barriers between technology and humans, even if RAs offer the best way to invest in normal situations.

A review of research on this topic highlights the importance of understanding investors' perspectives, designing transparent algorithms and customizing ARs to meet investors' specific needs. In fact, it is a tool that has been understudied in terms of consumer perception, either from a technology versus human perspective, or in terms of what the tool can offer or add value to the user.

Risk aversion is often mentioned as the main obstacle to using this tool, and many authors refer that RA would work better as a complement to investment professionals, rather than a substitute tool, since many investors also prefer to have human support rather than something completely mechanized. On the other hand, some authors focus on the way this tool is presented to consumers, moving into a marketing aspect, which may be the key for them to see this tool as something safe and likely to bring returns, increasing users' confidence in its use, and consequently decreasing their aversion to the tool and the inherent risk.

Furthermore, the investor's decision-making process ends up being influenced by RA, since it is RA that ultimately makes the decision on where to invest. With an algorithm behind it, some authors point out that this tool can help make more objective and concrete decisions, but it can also show biases. In this respect, another study shows that in the investment decision-making process, clients with greater difficulty in investment and financial matters tend to be more averse to this type of technology, preferring to opt for professionals in the field. Once again, a synergy between humans and RAs can be advantageous both for this tool to support investment advice and portfolio management when there is a large volume of data and several variables to take into account, enabling more informed and better-quality decisions, and to make the tool known to the user and enable them to use RAs independently through the time.

In more technical terms, there are RAs with different characteristics, models and algorithms that follow their target audience, i.e., the type of investor, and also the type of financial asset, be it cryptocurrencies, ETFs, shares, etc. The true essence of this tool is based on its strong predictive capacity, and this is where the models used come in. Some authors have pointed out that it is in fact difficult to predict this market, which is so volatile. Many authors refer to various types of ML models, such as neural networks, which are the most widely used.

In the meantime, many authors refer to the legal aspects of the tool, which must be transparent about the algorithms used and, in a way, protect its user, something that is considered very important and therefore worth mentioning in this article.

The way in which this topic has been approached in different countries also shows how different this tool can be and the different characteristics it can take on in order to be able to respond to its audience and reach more people, as well as adapting to financial assets. For example, in India investors prefer to have a more human contact, in Korea there is high financial literacy and a great interest in investing and there is a great opportunity for this type of tool.

The findings suggest that RA has the potential to provide low-cost financial advisory services, improve investment decision-making and contribute to the financial well-being of individuals, where a synergy between human and RA can result in a good match and provide much of what is needed to initiate an investment and manage it. In this sense, it is crucial to understand ways to improve the algorithm underlying ARs to attract more investor confidence and improve the tool to obtain better results, including improving the mathematical models and system architecture, which as seen above, the tool can adapt to each reality. Challenges related to ethics, fairness, privacy, governance and cognitive interaction must be taken into account in the development and implementation of ARs.

Research gap

The culture and ways of thinking of humans are intertwined with several factors. How humans think differs according to their country, the values they learned while growing up, and their traditions. Through this analysis, it is possible to observe that the data presented relate to studies carried out in countries outside Portugal and therefore are based on people from different cultures. In this sense, it is advantageous to understand how this tool has grown and its prospects in Portugal. This can be analysed by supporting the collection of surveys from the Portuguese population, namely potential investors, evaluating several socio-economic factors and understanding the influence of RAs in Portugal.

Additionally, these studies show a need to analyse the problems of RAs more precisely to efficiently move on to redesigning the system's architecture and the mathematical predictive models to be adopted.

Also, a study of the socioeconomic and human characteristics issues with mathematical models could be considered for further research. In general, a connection between improving a precision algorithm, which, besides the need to be improved technically as already referred, needs to meet society and consider various social aspects since the main target is the human being.

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Appendix A – Number of publications of each author. Source: VOSViewer software

Author	Documents
Kobets, V.	5
Savchenko, S.	2
Yatsenko, V.	3
Hinz, O.	2
Morana, S.	2
Alshater, M.M.	2
Khan, K.	2
Lee, J.	2