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Review article

The emerging field of Robo Advisor: A relational analysis

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A B S T R A C T

Robo advising is an emerging business model that aims to popularize investment advisory services by automating all the activities involved. The robo-advisor (RA) stream of research is relatively new, yet it has started to attract the attention of numerous scholars. This manuscript aims to analyze the academic literature on RA based on its impact on the different phases that make up the investment advice process. Our aim is to investigate which phases of the investment advice service prove of most interest to scholars. Since selecting relevant and precise keywords increases the visibility, accessibility, and indexing of a research paper, we explore the RA research landscape using keyword relational analysis. We analyze metadata from 195 identified papers combining the Scopus and Web of Science databases until May 2022. The analysis unfolds in two parts. First, we examine the relationships and associations of keywords in titles, abstracts, and author keywords to extract knowledge patterns from said associations. As a novelty, a specific dictionary of RA-synonyms formed by 19 disjoint families of concepts is obtained. The second part presents the RA's conceptual and relational structure. For this, five clusters are determined to identify and organize those studies dealing with similar topics. The results of our study suggest that research is more interested in aspects related to the human factor, namely, those with phases requiring more direct contact with the client or investor. The most relevant research interests include the automation of client profiling functions and client response to the latter automation.

1. Introduction

Technological changes are the main driver of productivity growth in all sectors of economic activity [1]. They have revolutionized production processes and customer services, so much so that we have become accustomed to naturally interacting with robots, machines, or chatbots. New technologies have also caused changes in consumer habits and created new needs that were previously unknown. Humans have access to such a volume of information that we are unable to process it, having to use algorithms or artificial intelligence when making decisions based on such an enormous amount of information. Furthermore, the globalization of knowledge has made new information technologies accessible to any business sector.

In the financial sector, the term Fintech appears, referring to all new technologies that improve or automate financial processes. So, Fintech is already present in practically all financial services: payment, investments, insurance, and loans [2]. Investment advice (IAd) is one of the services with the highest added value. Traditionally, this service was only offered to a niche of clients with a high level of wealth. With the arrival of Fintech, a new service known as robo advisor (RA) has been developed with a view to popularizing IAd.

RA service aims to transform and scale a niche business to a volume one [3]. The income growth expectations offered by this new

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advising method are very attractive for financial institutions. In 2022, the six largest RA managed over 20 billion U.S. dollars each. Assets under management in the RA market are expected to reach USD 1802.00bn in 2024. It is estimated that the value of the managed assets will continue to increase, and according to this forecast, in 2028, they will have increased to 2334.00bn U.S. dollars [4]. These data show that RA is a reality that is here to stay. Although RA offers significant advantages (low costs, accessibility, simplicity, transparency, and continuous monitoring), it also has limitations and risks that investors should be aware of when considering its use, such as lack of personalization or limitations in diversification [5,6].

This transformation of the IAd service poses great challenges that must be met [7]. On the one hand, the transformation towards a volume business affects all company departments involved in the IAd service. Some may even disappear due to the automation of all their functions. On the other hand, the application of new Fintech technologies changes the way of relating to the client or the tools used to carry out certain parts of the IAd process. Advances in Artificial Intelligence are opening up new possibilities for financial advice, not only with the development of RA but with the use of new chatbots such as ChatGPT [8], which have achieved good results.

This paper is motivated by the recent and growing academic literature analyzing the RA. Review studies are needed to advance the research, illustrate the status quo, and guide future research directions. Some studies in the literature analyze the main trends in global research on this new technology [9–12]. D'Acunto et al. [9] try to summarize current knowledge about RA without using a systematic literature review. Torno et al. [10] conduct a systematic literature review of 42 papers (30 articles and 12 conferences) that distinguishes three main themes: RA Users, RA Service, and RA Competence. Rico-Pérez et al. [11] investigate the main research topics and the most critical scholars, as well as the journals and countries in which this scientific research is being carried out. Cardillo and Chiappini [12] use a systematic literature review to analyze 103 articles on RA and identify four clusters of research on RA: early attempts to classify RA, behavioral topics, performance, and algorithmic modelization.

However, despite the attention paid to RA development by society and scholars in recent years, there has not been a comprehensive analysis of RA research interests and their relationship to the different phases of the investment advisory process. In this sense, the objective of this manuscript is to analyze the main topics related to the RA that have attracted the attention of academics, linking them to the advisory process. This makes it possible to identify which parts of the IAd service are the most studied and, therefore, the most affected by the implementation of the RA. We are interested in knowing whether a greater interest exists in those phases of the service in which there is more significant human intervention or in more automated ones. For this, a conceptual structure of the RA is defined a priori. Two main clusters*, C1-Low human factor* and *C2-High human factor,* are determined in order to group concepts according to their degree of relationship with human behavior. Subsequently, we add three clusters that allow us to complete the RA conceptual map: *C3-Compliance*, *C4-Cross RA business*, and *C5-General methodologies*.

In this paper, 195 academic documents have been revised to identify the challenges and opportunities surrounding the RA. Since the selection of relevant and precise keywords increases a research paper's visibility, accessibility, and indexability, we explore the RA research landscape using keyword relational analysis. Our motivation to employ a relational analysis in this study is that this type of analysis provides a more comprehensive understanding of the knowledge in the field under study and allows uncovering gaps in the literature as well as the identification of possible future research lines. Our interest has focused on analyzing the words included in the titles, authors' keywords, and abstracts of these documents to study the association between these words. These associations allow us to define the relationship between the clusters and the papers of our corpus. The present paper attempts to answer the following questions: (1) Which are the most significant research topics with respect to the RA? (2) Which RA-keywords are related to the different phases of the IAds? (3) Are the documents specialized in a unique cluster, or do they study more than one topic simultaneously? (4) Are authors focused on a specific cluster? (5) Which phases of the IAd service have focused the interest of researchers? (6) Does research focus on analyzing those problems that have more to do with the human factor within the RA service or on processes with a reduced dependence on the human factor? Answering these questions allows us to better understand the actual stage of RA research. We can easily find all the papers or authors focused on the different topics and clusters and identify possible research gaps.

As a novelty, a specific dictionary of RA synonyms is developed in this paper. Previously, a list of RA-stopwords was obtained. A list of stopwords is an inventory of concepts or words that are not useful when extracting the relevant keywords that summarize a research topic. The dictionary of RA-synonyms allows grouping all the words used to refer to the same topic into families of concepts. This is very useful for analyzing the relevance of the research topics. The analysis presented here is based on the relationship of the RA synonyms with the previously defined clusters, the articles, and the authors of our corpus. This relationship allows us to draw a complete concept map of the RA and the current situation of the RA research.

The contribution of this paper is as follows: (1) a dictionary of RA-synonyms and a list of RA-stopwords is developed that allows us to define word families that represent the main research topics, (2) a relational analysis is undertaken to review the main topics related to the RA that have attracted academic attention, linking them with the different phases of the IAd process, and (3) additionally, we create an open-source code that can be used by any other researcher interested in conducting a relational analysis on any research topic at any time interval.

The rest of the work is organized as follows. The next section will introduce our study's main concepts: Investment Advice and the Robo Advisor. The description of the applied methodology and the techniques used is included in section 3. Next, the analysis of keywords is presented in section 4. In Section 5, we define the clusters to which we want to relate the keywords and phases of the advising process. We relate the five clusters with the documents included in our corpus in Section 6. Section 7 discusses the findings and Section 8 provides the conclusions.

2. Theoretical framework

To understand the RA's impact on the IAd service, it is necessary to define the phases required to develop it. Beketov et al. [13]

consider that this process comprises five phases (see Fig. 1).

We need to evaluate the impact of the human factor on successfully completing each of these phases. Another aspect to consider when analyzing the emergence of RA is that in the traditional IAd model, these five phases are developed by different work teams within the financial institution. This complicates the transition to an automated model where all phases are developed within a single technology platform.

Phases 2 and 5 are usually the responsibility of the areas in charge of customers, as they require greater proximity to the client. In this sense, the impact of the human factor is twofold since, on the one hand, it is a task performed by a human being, but on the other hand, its objective is also to interpret the needs of another human being. Due to the high degree of human intervention in these process phases, their scalability to a larger number of customers is very low for the traditional model since it means proportionally increasing the number of people dedicated to this task. The objectives of these two phases are to identify the investor profile [14], which involves interpreting the client's needs or requirements as accurately as possible (phase 2), reviewing the results obtained, and analyzing whether they have met the client's expectations (phase 5). Phases 1 and 4 may involve different departments: portfolio management, strategy, and analysis, among others. Their main objective is to estimate the return and risk of a universe of assets and to interpret the impact of new variables that appear in these estimates. In these two phases, quantitative tools and teams of analysts are used to interpret the impact of market variables on expected return and risk. The human factor is, therefore, less important than in phases 2 and 5. In phase 3, the portfolio is built to meet the customer's expectations.

These five phases, necessary to build an IAd service, must be developed by the RA to offer the service to a large volume of customers.

One of the first definitions of RA appears in the Deloitte study [15], in which they define RA as 'new companies that accumulate information and algorithms to automate the allocation of portfolios and make personalized recommendations to the individual client'. This very general definition focuses on the appearance of these new Fintech specialized in the automated advisory service. However, it is already delimited as an IAd service.

With the development of the business and the increase in research, we can find other definitions that go a little deeper into the concept of RA, including details related to the platforms where they are developed or the use of algorithms. In this sense, Levine and Mackey [7] consider that 'RA are digital platforms that have interactive components and intelligent assistants that use information technology to guide clients in the financial advice process automatically'. This is an open definition but introduces concepts that help us visualize the keys to implementing an investment advisory model through RA. Concepts such as automation, smart assistants, and guiding customers help us to focus on where the key points in the implementation process are going to be.

Another definition in which we find more specific terms, such as quantitative algorithms, is that of Beketov et al. [13]: 'RA can be defined as an automatic investment platform that uses quantitative algorithms to manage investor portfolios and is accessible to clients online'.

All definitions consider RA as an investment advisory service developed or implemented on a platform. The new ways of relating to customers are also made explicit.

Jung et al. [16] compare an RA to online brokers. An RA differs from online investment platforms or brokers in the way it performs client evaluation and portfolio selection. This helps us better understand the innovation introduced by an RA.

Regarding the client evaluation, the RA changes the traditional Human–Human Advisor model to a Human–RA digital model and from a Human–Human bilateral process to online questionnaires and self-reporting. In the Human–RA model, RA almost substitutes for humans in the IAd process, as the algorithms evaluate investment objectives, risk aversion, or profitability expectations [17]. Thus, human interaction with the client is limited to situations unrelated to evaluating the investment profile or process, such as computer

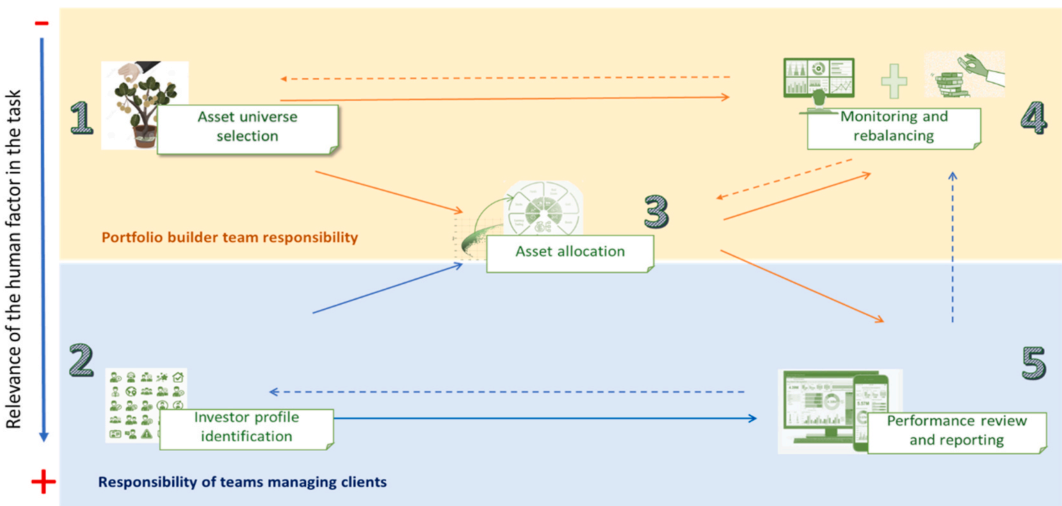

Fig. 1. Phases of the Investment Advice process, information flows, and human factor impact. Source: Own elaboration.

technical support or fraud management. The role of the client manager as an interpreter of the client's needs is eliminated.

Jung et al. [16] point out the change in the implication of the human factor in the identification of the investor profile (phase 2 of the IAd process), and the new Human–RA relationship appears. These authors identify the limits of human intervention. At the same time, they also mention the change it entails for phases 1 and 4, restricting the universe of assets that can be incorporated into a portfolio. For client portfolio management, RA relies on assets that require minimal active management, such as Exchange Trade Funds (ETFs), which are passively managed [18]. However, because not all investors base their investment decisions on a mean-variance criterion [19], instrument standardization reduces the ability of RA to find portfolios that meet clients' constraints or expectations. The future agenda for the RA business should include its evolution towards portfolios better suited to more personalized financial planning that use more complex financial instruments [18].

The RA market has experienced significant growth in recent years, with more consumers turning to automated platforms for investment advice. The reasons for this success are diverse: (i) a new generation of customers exists, most notably tech-savvy millennials, who prefer digital platforms for financial services, (ii) RA possesses several advantages over traditional financial advisors that are more expensive and may require higher minimum investment amounts, (iii) the presence of the growing popularity of passive investing, (iv) the existence of large-scale financial processes, and (v) the continued development of artificial intelligence and machine learning technologies [20]. Additionally, COVID-19 accelerated the shift to online financial services, including robo-advisors, so that more consumers turned to digital channels for their financial needs. Therefore, RA constitutes one of the most important disruptive trends in the asset and wealth management industry. In the coming years, the robo-advisor market is expected to grow, reaching a potential 34.130 million users by 2028 [4].

In the next section, we describe the data and methodology used in this paper.

3. Data and methodology

3.1. Data

The data analyzed in this study was retrieved from the Web of Science and Scopus, the most frequently used academic databases [21]. The period examined was until May 2022 (see Table 1). We have chosen Scopus and the WoS because their metadata structure is very similar, which allows their combination to build a single corpus. Hence, more information of a qualitative nature is available for the analysis to be developed [22].

The search conditions include all the research documents with the expression 'Robo Advi*' in their title, keywords, or abstract. With this query, all the documents that include these two words and all the combinations of 'advi*' are obtained from any part of their metadata (title, keywords, or abstracts).[1] The search is limited to documents in English. This query found 205 documents in the WoS and 144 in Scopus, some of them coinciding in both databases. So besides cleaning the data, we must eliminate duplicate papers. Once we merge the metadata of both databases, we obtain 219 unique references but only 195 with abstracts. These 195 papers form the corpus of our study (See Table 11 in Appendix).

According to our query, the oldest article, Chew [23], is from 2015. However, this article is not in our corpus as it does not meet the condition of having an abstract. Thus, the first article in our corpus, Britton and Atkinson [24], was published in 2016. During the period of our study, RA research increased considerably from 1 paper in 2016 to 56 in 2021 (see Fig. 2).

3.2. Methodology

The relational analysis in this paper was conducted using the R packages *Bibliometrix* [25] and *tm-Text Mining* [26] and our code.[2] This analysis evaluates the link between the documents and authors and the different research subjects in our corpus. The titles, the abstracts, and the author keywords have also been analyzed to find the relation between these research topics and the five phases of the IAd service. Applying the R packages *wordcloud2*,[3] *heatmaply* [27], *igraph*,[4] and *bipartite* [28] highlights the relationships between research topics, abstracts, and authors.

The first part of our analysis involves studying the relationships and associations of words in a set of documents to extract knowledge patterns from these associations [29]. Callon et al. [30] consider that keywords represent the set of topics the documents deal with and, therefore, can be used to measure the similarity between publications.

The second part consists of defining the RA's conceptual and relational structure. Five clusters have been determined to identify and organize studies related to similar topics. In this study, unlike other papers [31–33], these clusters have been defined a priori based on the advice of expert financial analysts.

[1] We used the asterisk (*) in the search as a wild card character to make our search simpler and more comprehensive as it tracks all the possible forms of the used terms.

[2] See https://github.com/hricope/Relational_Analysis.

[3] See https://cran.r-project.org/web/packages/wordcloud2/wordcloud2.pdf.

[4] See https://cran.r-project.org/web/packages/igraph/index.html.

Table 1
Search protocol.

Database	Period	Document Type	Search Criteria	Keywords	Nº of Documents	WoS + Scopus
WoS	Through May 2022	Article, Proceedings Papers, Review Articles, Book Chapter	Theme	"Robo Advi*"	205	219 different references and **195 references with abstracts**
Scopus	Through May 2022	Article, Conference Paper, Book Chapter, Review, Book	Article title, Abstract, Keywords	"Robo Advi*"	144	

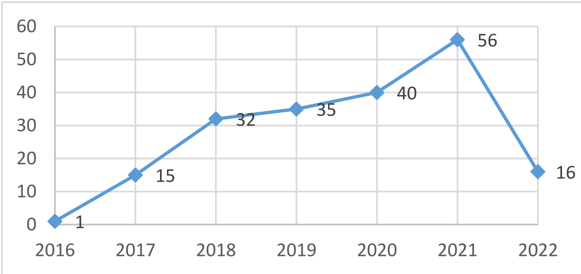

Fig. 2. Number of articles published yearly from 2016 to May 2022. Source: Own elaboration.

4. Co-word analysis: RA-stopwords and RA-synonyms

The analysis of keywords has been deepened to identify the most significant research topics regarding RA. For this, the keywords from titles, author keywords, and those obtained from abstracts are used.[5]

In this paper, two-word lists have been created to refine the analysis results. On the one hand, a list of RA-stopwords comprising a total of 1887 words that have no relevant meaning for the study was compiled. This list also includes words that, although having a relevant meaning, do not add value to the study; therefore, they are excluded from the analysis process. On the other hand, a dictionary of RA-synonyms has been created that incorporates 452 terms classified into 19 disjoint families of concepts. These families define all the RA processes and help to identify the lines of research present in the documents of our corpus. The objective is to link these families with the different phases of the IAd service presented in section 2.

The process for generating the RA-stopwords and RA-synonyms lists consists of three steps, as described below.

Step 1: Extraction of raw terms. Using the function *termExtraction* of the *bibliometrix* R-package, we extract a list of keywords from our database's titles, author keywords, and abstracts. Compound terms have been extracted from up to a maximum of 2 simple words (n-grams = 1 to 2).

Step 2: Creation of RA-stopwords list. When performing a bibliometric analysis based on keywords, having these stopwords in the preprocessing phase helps to obtain more focused results on the research subject since all those words that do not have a relevant meaning for the study are eliminated. Thus, greater visibility is given to those terms that provide more value and meaning to the issue under study.

In this paper, the authors have manually selected 1887 words or concepts considered irrelevant for the RA analysis. These words have been chosen from the total terms extracted in Step 1. Also, along with the stop words that arise by default in the *bibliometrix* R-package, all possible combinations of the terms Robo + Advi* have been included, given that it is our initial query. Author and country names have also been considered stopwords as they have no relation to the phases of the IAd process. All of these terms constitute our set of RA-stopwords.[6]

Step 3: Creation of RA-synonyms list. This dictionary facilitates the analysis of the relevance of the different issues covered in the RA research by allowing all those words that refer to the same topic or concept to be grouped into families. Thus, after eliminating the list of RA-stopwords, 5179 words were obtained from the titles, the author keywords, and the abstracts. Of them, 452 words have been selected manually by the authors. In this review and selection process, we consider each word's frequency of occurrence.

We consider these words representative of all those topics of interest for the RA analysis. We refer to that new word list throughout this paper as Robo Advisor Keywords (RA-Ks). The RA-Ks have been grouped into 19 families: Asset Allocation, Instrument Markets, Risk Performance, Quantitative Methods, Behavioral RA Acceptance, Humanization, Decision Making, Customer Interaction, Compliance, Finance Advisory, Fintech, Innovation, RA Implementation, RA Players, Artificial Intelligence, Algorithms Digitalization, Automated Investment, Blockchain and Big Data (see Tables 6–10 in Appendix). These conceptual groups have also been identified

[5] We have considered the title, the abstract and the author keywords of the documents in our corpus as representatives of their content. The title should be concise and transmit the main topics of the study and highlight the importance of the research, the abstract must have its own entity and be a guide to the most important parts of the paper, and the author keywords must represent its content.

[6] The RA-Stopword list can be requested from the authors.

with the five phases of the IAd process (see Fig. 1). This allows us to examine the relevance of each of these phases in the documents collected in our corpus. When analyzing the frequency of the RA-Ks, we observe that their domain goes beyond the five phases of the IAds. It is, therefore, necessary to define a larger number of word families to cover all the lines of research represented in our corpus.

Figs. 3–5 display the graphic representation of the keywords in each step of this cleaning and grouping process. Fig. 3 shows the 200 most repeated words when working with all the keywords extracted from the titles, the author keywords, and the abstracts. We can see that generic words related to the performed search appear, such as 'financial', 'robo advisors', or 'investors'. When applying the RA-stopwords, we exclude those words that are not significant for our study or have been used for the initial search, such as robo advisor. The results are shown in Fig. 4, in which more specific words such as 'investment', 'portfolio', 'risk', or 'digital' stand out. Finally, when applying our RA-synonyms, the process produces results that are more oriented to the objectives of this study. Thus, Fig. 5 shows terms such as 'Asset Allocation' or 'Behavioral RA Acceptance' that can be clearly linked to Phases 2 and 3 of the IAd service.

In the next section, we define the clusters to which we want to relate the 19 RA-Ks families and the phases of the advising process defined by Beketov et al. [13].

5. Conceptual structure: clusters

We wanted to determine which phases of the IAds the researchers are most interested in. Also, we wished to see if the research focuses on analyzing those problems that have more to do with the human factor within the RA service or, on the contrary, they focus more on quantitative processes with reduced dependence on the human factor. To meet both objectives, we defined five clusters. Once this manual phase was completed, we processed the whole corpus using the code we developed in R to complete the relational analysis.

5.1. Clusters definition

After consultation with financial experts, the authors manually defined the clusters considered in this study. First, two main clusters, *C1-Low human factor,* and *C2-High human factor*, were defined to group concepts according to their degree of relationship with human behavior. These two clusters are related to the five phases of the IAd process.

- *C1-Low human factor.* This cluster includes concepts less related to the human factor, such as the calculation of risk-return, selection of assets, estimation, and other quantitative methods used in Phases 1, 3, and 4 of the IAd process (selection of the universe of investments, asset allocation, and rebalance). The financial institution's departments involved in these phases are analysis, strategy, quantitative, and portfolio management.
- *C2-High human factor.* The second cluster has been attributed a greater weight to the human factor. The investment advisory phases related to this cluster are Phase 2, the definition of the investor profile, and Phase 5, the analysis of performance and reporting to the client. In traditional investment advice, these phases that require more direct contact with the client or investor are carried out by those departments responsible for the clients or commercial force of the financial institution.

After analyzing and reading the 195 abstracts in our database and based upon the advice of the experts consulted, we noted the need to include three additional clusters, which allowed us to complete the RA conceptual map.

- *C3-Compliance.* This cluster includes all the issues related to the regulatory aspects that derive from the implementation of the RA. It is not directly related to any of the phases of the IAd process.
- *C4-Cross RA business.* This cluster's content is more heterogeneous. It includes all the cross-cutting issues related to the business and management implementation of an RA model. It is not related to any of the phases of the IAd service.
- *C5-General methodologies.* Finally, a cluster dedicated to the general methodologies applied in the development of the RA is defined. It includes the importance of the different technological issues and the algorithmic tools used in RA.

5.2. The Robo Advisor Keywords and clusters relationship

Once the clusters have been defined, it is necessary to relate them to the RA-Ks obtained previously. For this, the 19 families of RA-synonyms are distributed among the clusters so that a family can only belong to a single cluster (see Table 2). For example, the cluster C3 has assigned the family of synonyms 'Compliance' that includes terms or concepts such as *bank-regulatory-compliance, data-privacy, fear-of-investment-fraud, fiduciary-duty, Korean-law, law,* and *legal-informatics* (see Table 8 in Appendix). Fig. 6 presents the complete conceptual map, with the RA-synonyms, the 19 families, and the five clusters.

To measure the relevance of each cluster, the RA-Ks associated with each one have been counted. Each RA-K belongs to one of the 19 families and, therefore, to a single cluster. However, each word can appear in several abstracts[7] of the same cluster (see Table 3).

C1-Low human factor. The RA-Ks of this cluster appear 959 times in the abstracts, representing 30.1 % of the total. The most relevant family within this cluster is the 'Asset Allocation' and all its synonyms, mainly related to portfolio management or investing. Therefore, concepts related to portfolio optimization, such as Markowitz, mean-variance, and Black Litterman, among others, appear. All these

[7] Although we refer to abstracts, our work has been carried out taking into account the words present in the titles, author keywords and abstracts of our corpus.

Fig. 3. Top 200 keywords in Step 1. Source: Own elaboration with *wordcloud2*.

Fig. 4. Top 200 keywords in Step 2. Source: Own elaboration with *wordcloud2*.

Fig. 5. Keywords with a frequency higher than 24 in Step 3. Source: Own elaboration with *wordcloud2*.

concepts are focused on phase 3 of the IAd process, the allocation of assets or construction of the appropriate portfolio for the client's profile. In this regard, it seems that RA seeks to solve the same problems with the same tools that human teams use but incorporating automation and the capacity to manage a greater number of portfolios.

The second relevant family refers to 'Risk Performance'. Since the asset allocation problem is focused on achieving the expected return and the risk accepted by the investor, this is another of the classic problems that analysts face. The challenge for the RA is how to automate this task for a large number of different clients.

The third family by relevance is 'Instruments and markets', which covers the assets and markets in which the robo advisors operate. This allows us to verify that the most mentioned financial assets are those related to funds, mainly ETFs. This is because working with investment funds, including ETFs, simplifies the estimation of the return and risk of the assets since variables, such as dividends, coupons, or maturity, are eliminated in the estimation model [34]. This allows automating this part of the process, although it reduces the diversity of assets to consider in the portfolios [16].

Finally, in this cluster, we include a family of concepts related to quantitative methods, which are applied in phases 1, 3, and 4 of

Table 2
RA-cluster, RA-Ks families, and Investment advice phases.

Cluster	Family	Family Description	IAds phases & other RA relevant issues
C1-Low Human factor	Asset_Alloc	IAd phase 3: issues related to customer portfolio construction and the different methods used.	1-Asset Universe Selection. 3-Asset Allocation. 4-Monitoring & Rebalancing.
	Instruments_Markets	IAds phases 1: issues related to the financial instruments available for UNIVERSE SELECTION.	
	Risk_Performance	IAds phases 1,3,4: issues related to measuring instruments & portfolio performance and risk.	
	Q_Methods	IAds phases 1,3,4: Quantitative methods.	
C2-High Human factor	Behavioral_RA_Acceptance	IAds phases 2,5: Issues related to the acceptance of the RA by the Human.	2-Investor Profile Identification. 5- Performance review & Reporting.
	Humanization	IAds phases 2,5: Issues related to the humanization of technology.	
	Decision_Making	IAds phases 2,5: Issues related to human judgment and decision making.	
	Custumer_interaction	IAds phases 2,5: Issues related to investor or client profiling.	
C3-Compliance	Compliance	Regulatory issues: issues related to regulatory or legal concerns about RA implementation.	Regulation Risk.
C4-Cross RA Business	Finance_Advisory	Words representing the financial advisory as the main goal of the RA.	General RA. Business Issues. RA Implementation. Business Model.
	Fintech	Fintech as the general field of new technology for finance.	
	Innovation	Words that represent technological innovation.	
	RA_Implementation	Words that represent concerns about the implementation of the RA business model.	
	RA_Players	Words representing leading players in the RA business.	
C5-General methodologies	AI	Words related to Artificial Intelligence applied in any phase of the RA implementation.	Methodologies not specific to the IAds phases but mentioned in a general way in the corpus analyzed.
	Algorithms_Digitalization	Words representing digitalization or automatization.	
	Automated_Invest	Words representing service automatization.	
	Blockchain	Words representing blockchain methods or crypto assets.	
	Big_Data	Words representing data management.	

Source: Own elaboration.

the IAd service, where the human factor is very low. This family includes concepts such as bootstrapping, smart beta, regression trees, exponential moving average, etc. The lower weight of this family indicates that applying these methodologies does not generate great controversy in the implantation of RA.

C2-High human factor. The RA-Ks in this cluster appear 587 times in the corpus, representing 18.5 % of the total. This cluster focuses on understanding the importance of the relationship with the human being when developing an RA system. This relationship is of great importance when developing an RA system. While robo advisors are an automated platform, the human element plays a crucial role in ensuring the effectiveness and success of such systems. The most relevant families in this cluster are 'Decision Making,' with words such as choice, decision, or judgment, and 'Customer Interaction,' with words such as customers, personalized, social trading, or client.

After these two families, the following most named are the ones we have called 'Behavioral' and 'Humanization'. In the first one, concepts related to human behavior are grouped, for example, trust, perceived or human vulnerability, and in the second, concepts such as, human based, adoption, human machine or chatbots appear.

Finally, a specific family has been included that allows inquiring about the acceptance of RA, 'RA Acceptance,' in which concepts such as adoption, technology acceptance, emotion regulation, or machine-human interface have been included.

C3-Compliance. This third cluster is dedicated to regulatory issues. With 6.3 % of the RA-Ks, it has the least weight. Despite this, its presence as an independent block shows that the rise of a new business model, in which decision-making is left to algorithms or artificial intelligence, gives rise to regulatory issues that are already worrying RA researchers. This cluster comprises a single family in which terms such as regulatory, disclosure, legal, rights, or law are included.

C4-Cross RA business. The weight of this cluster over the total RA-Ks is 24.6 %, being the second in importance. As RA employs innovative methodologies, it is unsurprising that among this cluster's five families of synonyms, the most prominent is 'Innovation', which includes concepts such as technology, innovation or disruptive. The family 'RA Implementation' also stands out, in which there are terms such as business model, usability, crowdfunding, retail investors, and sandbox.

C5-General methodologies. With 20.4 % of the total RA-Ks mentioned in the corpus, this cluster becomes the third in relevance. Its most important family is that of 'Algorithms Digitalization' with concepts such as digital, algorithms, computer, or autonomous system. As expected, the 'AI' family has a high number of mentions. Concepts such as machine learning, neural networks, artificial intelligence, or deep learning are mentioned in a large part of the works in our corpus since they are transversal concepts throughout the RA.

Analyzing how the 19 RA-Ks families are distributed in the five clusters has allowed us to identify each one more clearly. In the

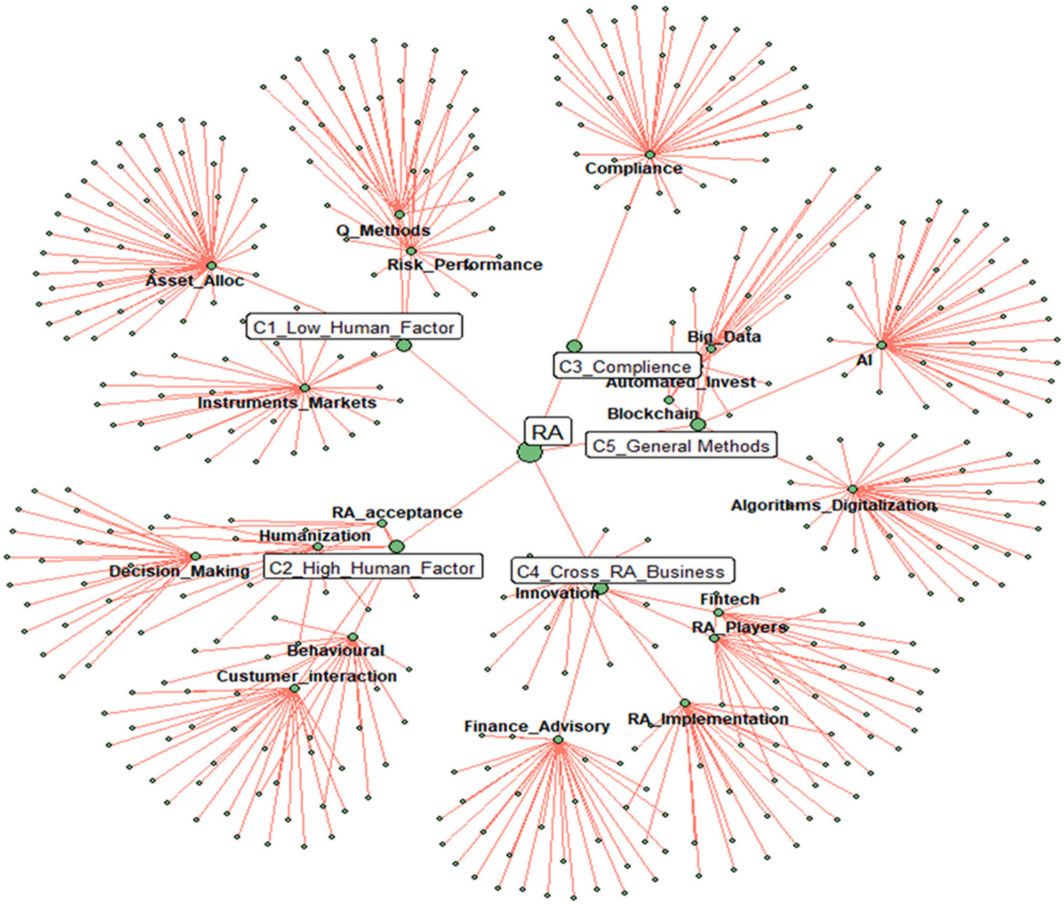

Fig. 6. RA conceptual representation. Source: Own elaboration with the *ggraph R-library*.

Table 3
Clusters relevance through RA-Ks.

Cluster	Nº RA-Ks Appearances	% Appearances
C1-Low Human Factor	959	30.1 %
C2-High Human Factor	587	18.5 %
C3-Compliance	201	6.3 %
C4-Cross RA Business	784	24.6 %
C5-General Methodologies	650	20.4 %

Table 4
The specific references of each cluster.

Cluster	References
C1-Low Human Factor	AB12, AB20, AB43, AB79, AB97, AB99, AB104, AB115, AB116, AB126, AB145, AB152, AB160, AB166, AB180, AB181
C2- High Human Factor	AB14, AB16, AB32, AB39, AB47, AB50, AB60, AB62, AB63, AB66, AB92, AB101, AB108, AB110, AB111, AB118, AB123, AB128, AB131, AB132, AB137, AB140, AB141, AB144, AB146, AB154, AB157, AB158, AB168, AB171, AB173, AB175, AB178, AB183, AB186, AB189
C3-Compliance	AB5, AB18, AB26, AB38, AB42, AB48, AB72, AB76, AB84, AB96, AB98, AB106, AB117, AB159, AB193, AB194
C4-Cross RA business	AB7, AB10, AB15, AB23, AB28, AB31, AB40, AB45, AB57, AB67, AB78, AB80, AB85, AB95, AB119, AB121, AB124, AB127, AB130, AB134, AB135, AB149, AB151, AB167
C5-General Methodologies	AB129, AB147, AB172, AB177

following section, we relate the five clusters with the documents included in our corpus.

6. Relational analysis

In this section, we relate the five clusters with the fundamental variables of our corpus, abstracts and authors. These relationships allow us to understand where the main focuses of scientific interest are and which parts of the RA process they affect.

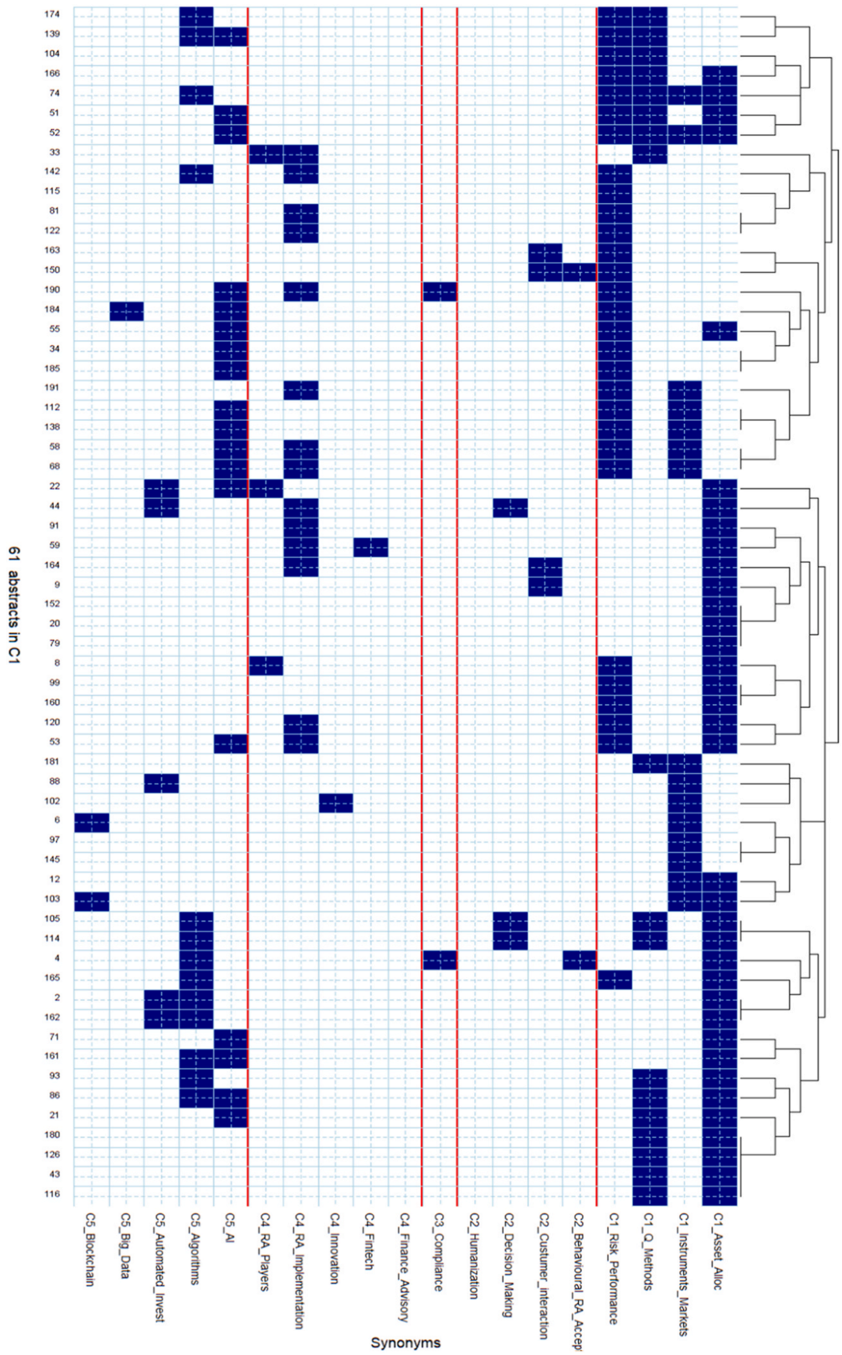

Fig. 7. Heatmap for references in cluster C1. Source: Own elaboration with the *bipartite R-library*.

6.1. Clusters and abstracts relationship

This subsection analyzes the relationship between the abstracts and the five clusters with a view to deepening their relevance. From Table 4, we conclude that 96 documents are included in only one cluster. Therefore, 99 papers are included in various clusters. We highlight that three papers are included at the same time in four of the five clusters: AB4 [35] appears in C1, C2, C3, and C5, AB54 [36]

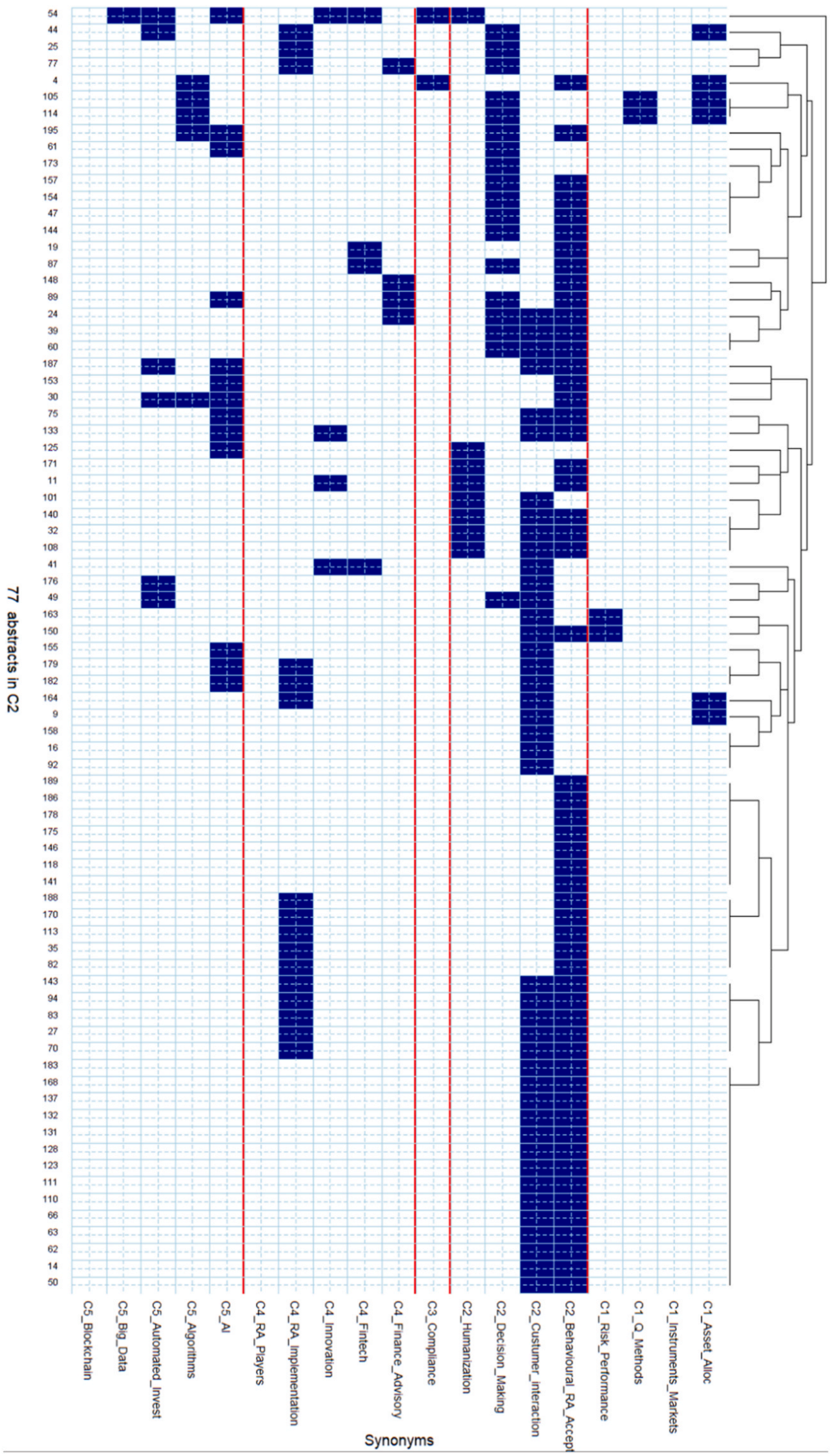

Fig. 8. Heatmap for references in cluster C2. Source: Own elaboration with the *bipartite R-library*.

is present in C2, C3, C4, and C5, and AB190 [37] is in C1, C3, C4, and C5.

Next, a heatmap of all the documents in our corpus has been developed to illustrate the relationship between abstracts and clusters.

C1-Low human factor. There are 61 references, 31.3 % of the total, dealing with topics related to C1, of which 16 focus exclusively on it (see Table 4 and Fig. 7). There are only two references that include issues related to C3, and eight that contain C2 concepts related to the families 'Behavioral RA Acceptance', 'Customer Interaction' or 'Decision Making'. Of the remaining references, most share concepts with the two groups that deal with more general or cross-cutting issues, C4 and C5.

C2-High human factor. We found 77 abstracts, 39.5 % of the total, dealing with human factors. This cluster has the highest number of documents, 36, specialized only in it (see Table 4 and Fig. 8). The RA-Ks most mentioned in these abstracts are those related to the families 'Behavioral RA Acceptance' and 'Customer Interaction'.

The paper of Gomber et al. [38], the most cited reference in our corpus, belongs to this cluster. This article covers topics related to

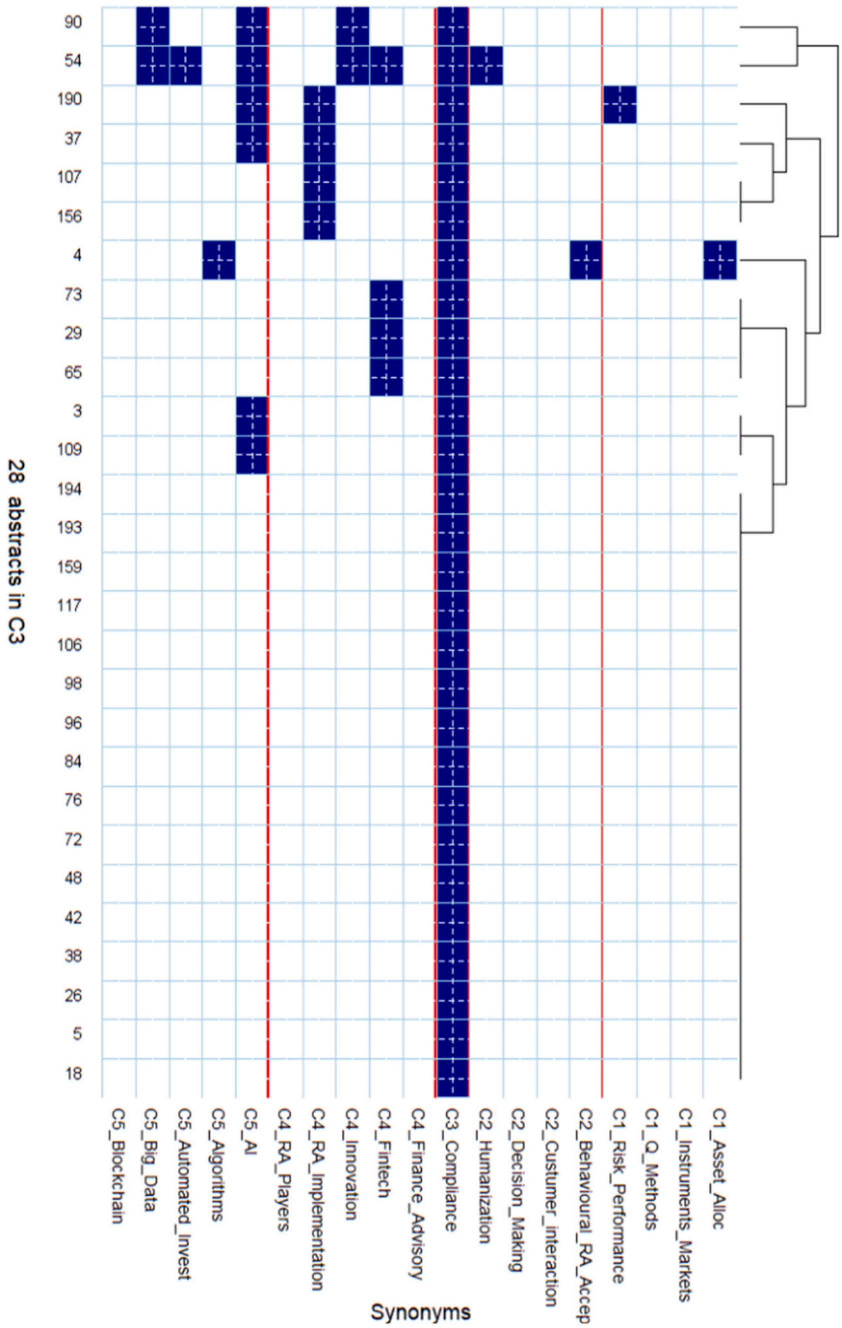

Fig. 9. Heatmap for references in cluster C3. Source: Own elaboration with the *bipartite R-library*.

'Customer Interaction' and others more transversal to the entire RA included in cluster C4, such as 'Fintech' and 'Innovation'.

C3-Compliance. We find 28 references in this cluster, 14.4 % of the total. According to our RA-Ks analysis, 16 stand out for dealing exclusively with regulation (see Table 4 and Fig. 9). Only two papers from cluster C1 (AB190 [37] and AB4 [35]) and two from cluster C2 (AB54 [36] and AB4 [35]) are related to cluster C3. This reflects the high specialization of the three clusters, C1, C2, and C3.

In this cluster, we highlight the paper of Baker and Dellaert [39], which was among the top 20 articles with the most citations. This

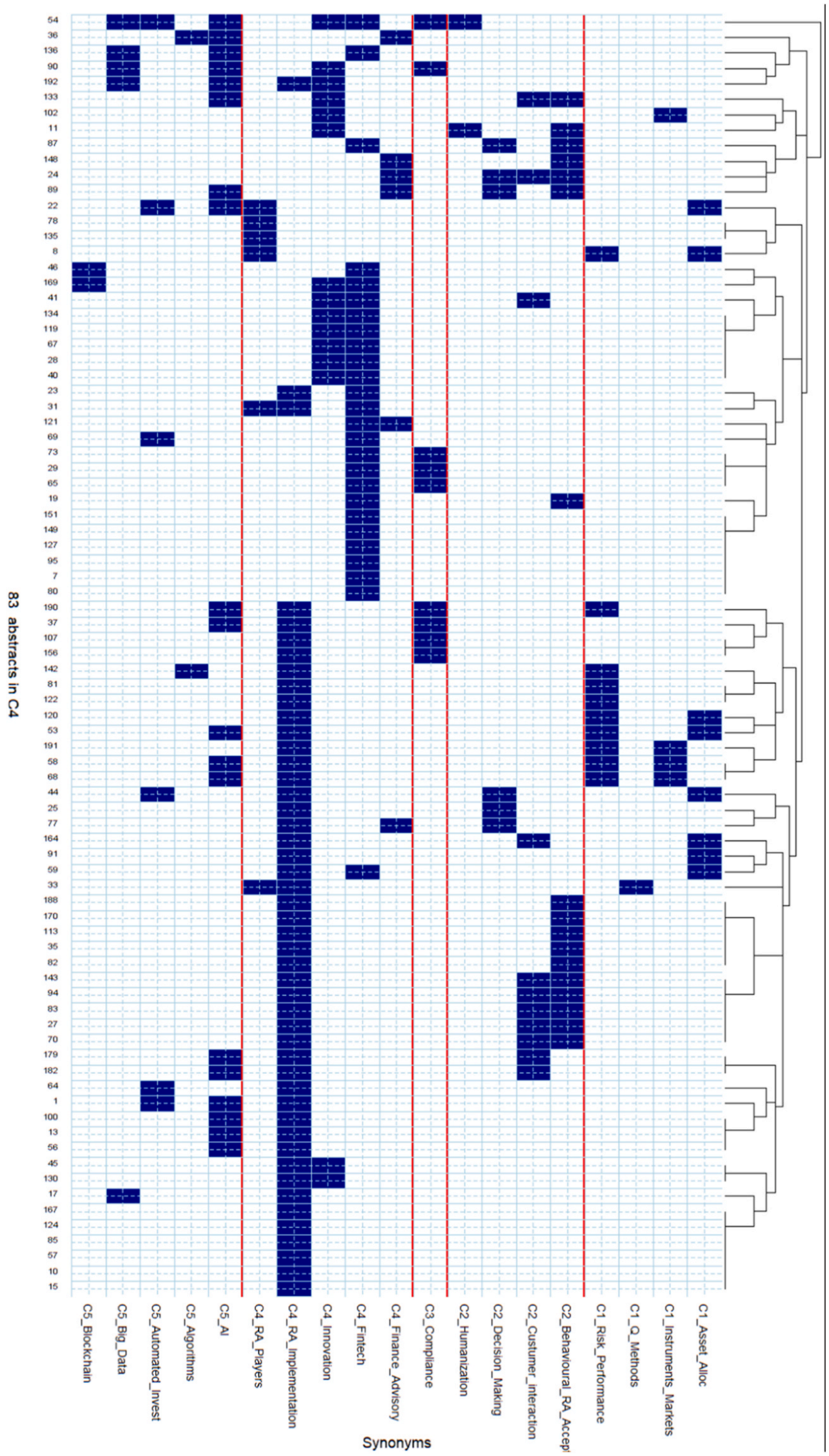

Fig. 10. Heatmap for references in cluster 4. Source: Own elaboration with the *bipartite R-library*.

paper presents the new challenges that RA poses to regulators. The authors show the advantages of RA, such as honesty or effectiveness in recommending suitable products, but they also identify new types of risks the regulator faces. In addition, they propose new capacities regulators must acquire to face this new form of advice where humans reduce their participation to a minimum.

C4-Cross RA business. This cluster is related to the highest number of abstracts, 83 references, or 42,5 % of the total. Considering that the topics in this group are transversal to the entire RA, it seems logical that most articles refer to some families that define it. Only 24

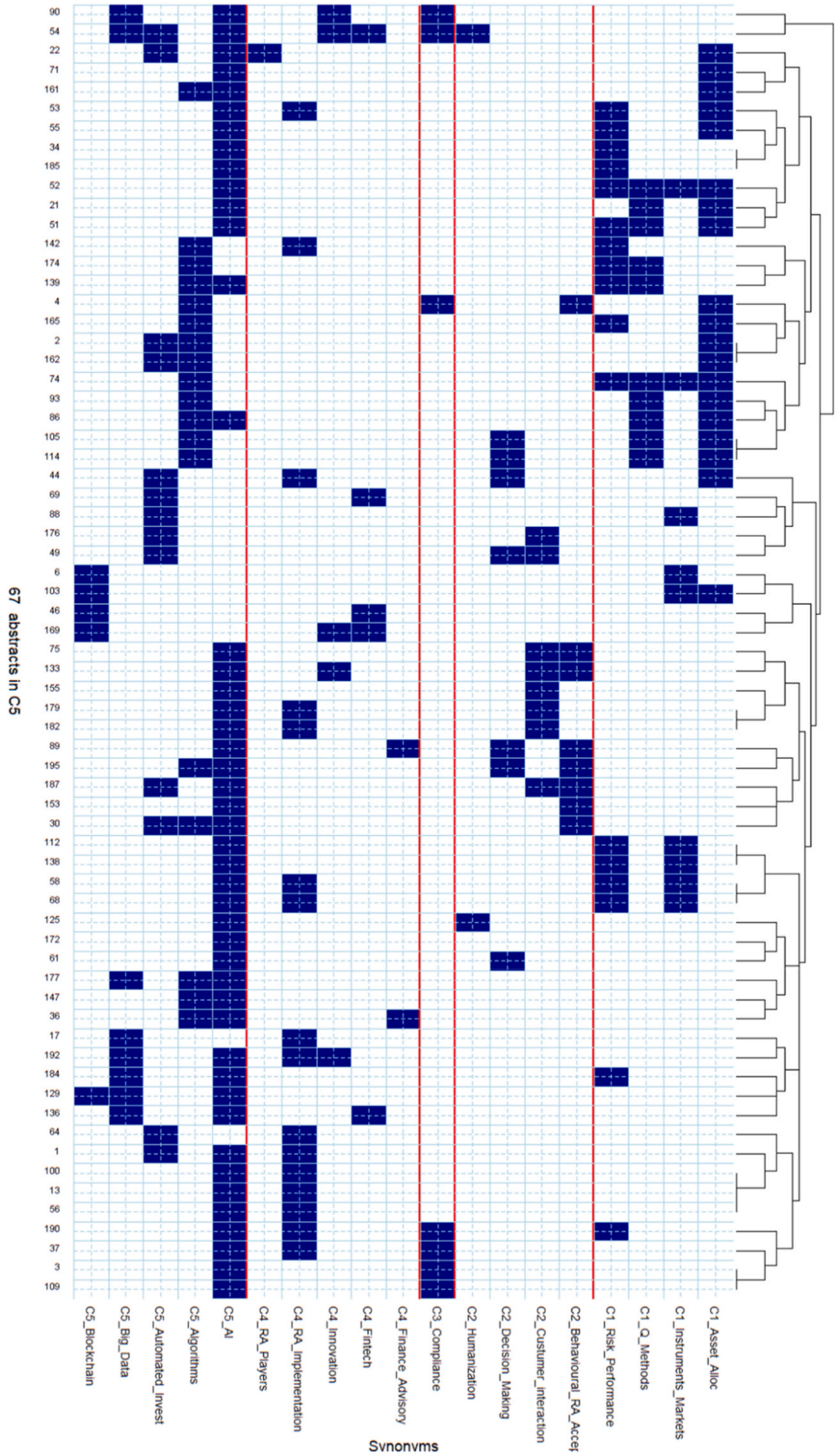

Fig. 11. Heatmap for references in cluster C5. Source: Own elaboration with the *bipartite R-library*.

references exclusively deal with topics included in this cluster (see Table 4 and Fig. 10).

In this cluster, we highlight the study of Chen et al. [40], the second most cited study in our corpus. Its main themes are 'Fintech' and 'innovation'. Fig. 10 highlights the family 'RA implementation' as the most mentioned. Considering the youth of the RA as a business model, it is reasonable that much of the research is devoted to its implementation problems.

C5-General Methodologies. This cluster includes general concepts related to new technologies. 'AI', 'Algorithms', or 'Digitalization', are the most relevant families of this cluster. Sixty-seven references deal with these topics, accounting for 34,4 %, but only four abstracts are focused on C5 (see Table 4 and Fig. 11).

In summary, we highlight that clusters C1, C2, and C3 have a high level of grouping, which means some references specifically investigate the topics in these clusters. The results for clusters C4 and C5 do not show such a clear grouping, which is because either the definition of their contents is transversal to all RA research or because they deal with general methodologies.

To sum up, articles of cluster C1 that deal with topics related to phases 1 (selection of the universe of assets) and 4 (rebalancing and assignment of portfolios) do not study issues related to phase 2 (profiling of clients) associated with cluster C2. Only eight abstracts (see Fig. 8) are related simultaneously to clusters C1 and C2, which indicates the high degree of specialization of RA research.

After analyzing the RA-Ks and the abstracts, we study the authors' relationships with the clusters and their associated RA-Ks families in the next section. The objective is to identify the authors who investigate each subject and thus determine whether the authors specialize in a particular cluster or topic or, on the contrary, whether the RA as a whole is investigated.

6.2. Clusters and authors relationship

The first step in this clusters-authors relationship analysis is to relate the 418 authors in our corpus with the 19 RA-Ks families and the five clusters. Fig. 12 shows a relational graph between authors and clusters. A group of specialized authors can be found for all clusters except C5. A high degree of specialization of the authors is observed; 43.7 % being specialized in a single cluster. The topics, in order of relevance, on which these groups of specialized authors investigate are the acceptance or modification of human behavior by interaction with a Robot (C2, 14.8 %), the implementation of the RA business (C4, 14.4 %), the problem regarding the estimation of profitability, the risk, and the portfolio construction (C1, 10 %), and the challenges faced by the regulation or compliance of companies that implement RA as a business (C3, 4.5 %).

Next, we analyze the research of the most cited authors of our corpus (top 20). To carry out this analysis, the methodology of Dormann [41] has been applied and implemented in the R-library *bipartite*. The results are shown in Fig. 13. Again, the results highlight that clusters C1 and C2 are usually studied separately; those authors who focus their research on cluster C1 do not usually deal with issues related to cluster C2 and vice-versa. We also observe that only two authors, Chen K and Hornuf L, are specialized in research on a single cluster, in their case *C4-RA implementation*. They analyze the evolution and impact of technological innovation in the financial

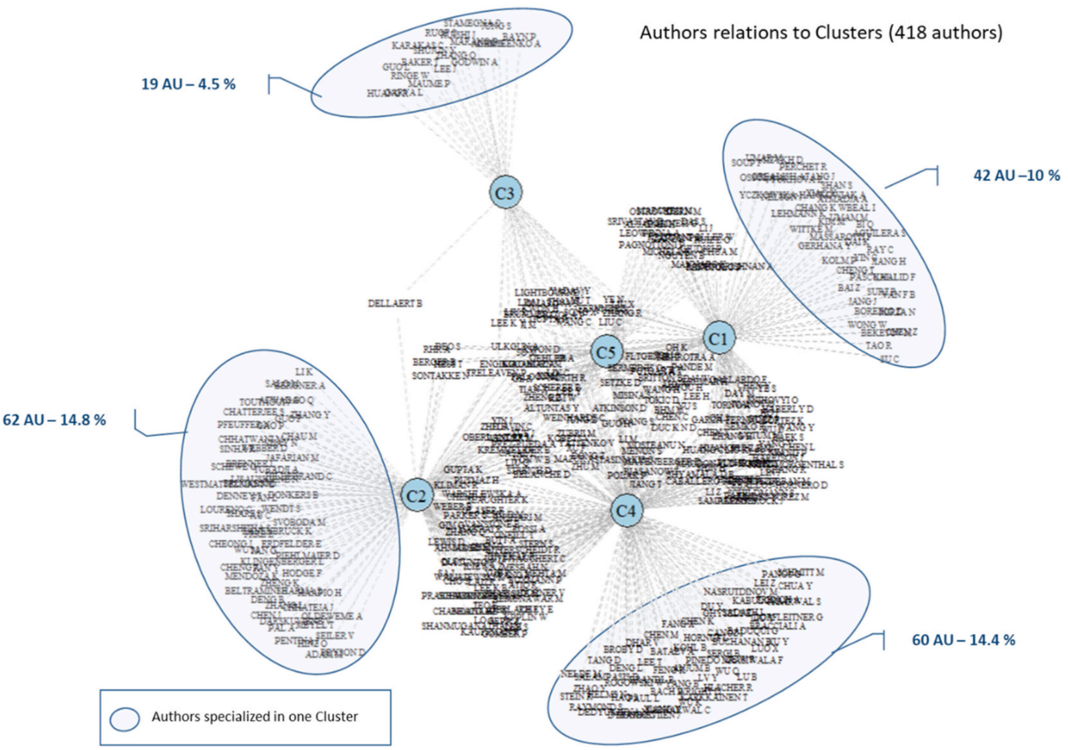

Fig. 12. Authors universe related to conceptual clusters. Source: Own elaboration with the *igraph R-library*.

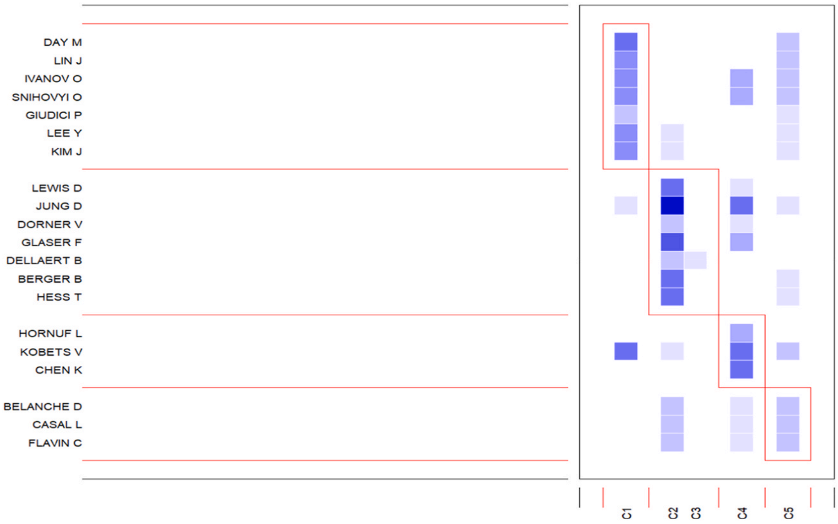

Fig. 13. Interaction matrix for 20-top authors and clusters. Own elaboration with the *bipartite R-library*.

sector. Hornuf focuses on the German market. It commences with mobile banking, evolves to trading and investment systems, and finally to insurance markets. They also review the problems of cybersecurity. The remaining authors deal simultaneously with the issues of different clusters. Jung D and Kobets V stand out as the most transversal authors. Their studies consider topics included in all the clusters except the one related to regulation (C3). Among the 20 most cited authors, only Dellaert B deals with regulatory aspects [39]. In his paper, the authors identify the issues to which the regulator must respond when implementing robo-advisors. From the moment an RA offers advisory services to thousands of investors, new questions arise about the liability of the service.

Table 5 shows the abstracts of the 20 most cited authors listed in Fig. 13. Three authors published only one paper. The rest appear with more than one paper, with Jung D and Kobets V standing out as co-authors of five papers. Likewise, among the 20 most cited authors, some have published together, such as Ivanov O and Snihovyi O, who collaborated on three papers. Kobets V is co-author of three papers with Snihovyi O and Ivanov O. The papers are related to the practical implementation of RA with different IA techniques (machine learning and neural networks). The other two co-authored documents are focused on solving the problem of consumption-saving ratio using RA. Jung D's studies are focused on identifying and solving the problem of adopting the RA service by investors. Decision inertia and biased financial decisions are the main issues to be resolved.

6.3. Research interest evolution

We start the analysis of the evolution of research interests in 2017 since it is the year in which a representative number of papers emerge. In 2016, there was only one paper in our corpus, Britton and Atkinson [24], which mainly deals with the implementation problems or business impact of asset management. Fig. 14 shows the evolution of research interest through clusters during the study period. As expected, C4 related to RA implementation stands out as the most important from 2017 to 2019. C2, which includes all the topics highly related to human aspects, grew in interest over the years until it became the main research topic in 2021 and one of the most important in 2022 [42]. This suggests that issues such as the automation in the definition of the customer profile (Phase 2 of the RA process) or the acceptance of RA by the investors are the main challenges on which research is focused.

Table 5
The specific references of each 20-top author.

Author	Abstracts	Author	Abstracts
Day M.	AB20, AB21, AB55	Glaser F.	AB39, AB77, AB83
Lin J.	AB21, AB55	Dellaert B.	AB42, AB123
Ivanov O.	AB33, AB34, AB68	Berger B.	AB49, AB60
Snihovyi O.	AB33, AB34, AB68	Hess T.	AB49, AB60
Giudici P.	AB103	Hornuf L.	AB7, AB121
Lee Y.	AB105, AB116	Kobets V.	AB25, AB33, AB34, AB68, AB91
Kim J.	AB105, AB116	Chen K.	AB28, AB31
Lewis D.	AB24, AB47	Belanche D.	AB57, AB187
Jung D.	AB27, AB39, AB44, AB77, AB83	Casal L.	AB57, AB187
Dorner V.	AB27	Flavin C.	AB57

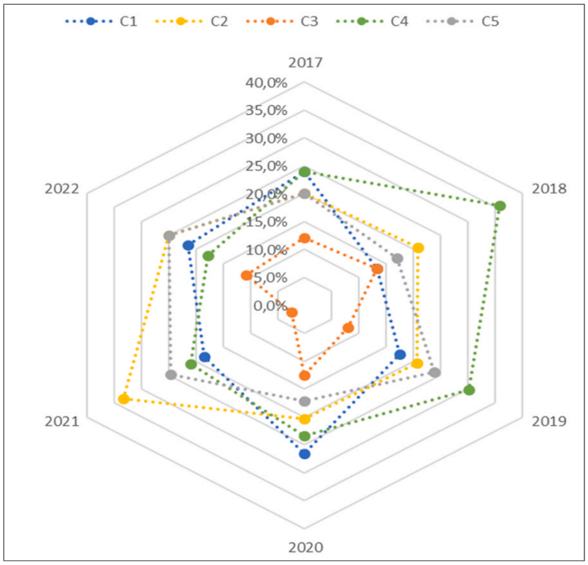

Fig. 14. Yearly evolution of research interest through clusters. Measured as a percentage of the total abstract universe. *2017 until May 2022. Source: Own elaboration.

7. Discussion

The irruption of automated investment advice has sparked a change in the form and processes of investment advice in the business of financial institutions. As in other occasions, this irruption of a technological change impacts or modifies the ways of performing jobs previously in human beings' hands. Investment advice is a process that is necessary to deal with human beings since its main objective is to match an investment portfolio to a client's risk profile. The new technology makes it possible to offer a high-value-added service to more clients. This has been achieved based on the standardization and automation of parts of the process, which makes it possible to reduce the costs of the process and, therefore, turn it into a higher-volume business.

The research we propose arises from the conclusions of several authors regarding the type of model suitable for the development of Robo Advisory (RA). In this regard, Bartlett and McCarley [43] conclude that 'an automated methodology plus an imperfect human, combining their decisions or judgments optimally, can outperform decisions made independently by an automated model or a human being'. This is one of the lines of research mentioned as open in the RA literature. In this sense, we believe it is important to know whether there is more academic interest in those phases of the IAds process where there is more human intervention or in those phases where there is more automation.

In this study, we have taken a unique approach by reviewing all the documents published until May 2022 regarding RA in international journals, conferences, and books accessible in the Web of Science and Scopus databases. Our primary objective was to systematically review the studies conducted, linking the different lines of RA research to the stages of the investment advice process. This approach has allowed us to identify the parts of this service that have been most analyzed following the transformation brought about by the implementation of RA, thus providing a fresh perspective on the topic. The following research questions were used to analyze the study's results: (1) Which are the most significant research topics with respect to the RA? (2) Which RA-keywords are related to the different phases of the IAds? (3) Are the documents specialized in a unique cluster, or do they study more than one topic simultaneously? (4) Are authors focused on a specific cluster? (5) Which phases of the IAd service have focused the interest of researchers? (6) Does research focus on analyzing those problems that have more to do with the human factor within the RA service or on processes with a reduced dependence on the human factor?

To answer the first question, we extracted all relevant words related to RA from our corpus's titles, abstracts, and author keywords. From them, we elaborated a dictionary of synonyms that we considered to represent all the issues of interest in the study of RA. These RA-keywords have been grouped into 19 disjoint families representing different topics. The results are presented in Tables 6–10 in Appendix, which shows the families and their synonyms. After consultation with financial experts, five clusters are manually defined. The *C1-Low human factor*, which includes those concepts less related to the human manual factor such as Risk-Return calculation, asset selection, etc.; *C2-High human factor* related, dedicated to everything related to behavioral finance, investors' desires and those actions in which the human factor plays a significant role; *C3-Compliance*, including topics related to the regulatory aspects of RA; *C4-Cross RA business*, including all those cross-cutting topics related to the implementation of a RA model; and *C5-General methodologies*, dedicated to the general methods applied in the development of RA. Analyzing how the 19 RA-Ks families are distributed in the five clusters has allowed us to understand each one more clearly.

To answer the other questions, we used the information in Table 2, which showed the IAds phases related to the clusters and RA-Ks families (the second question). Identifying the conceptual groups with the phases of the IAd process allowed us to study the relevance of each of these phases in the research collected in the corpus. The results of the study of the relationship between the RA-Ks and the clusters indicate that cluster C1 is the one that has the greatest weight within the total RA-Ks. The RA-Ks of this cluster appear 959 times in the abstracts, representing 30.1 % of the total. In second place appears the cluster C4, with a weight of 24.6 %. We analyze the relationship between the abstracts and our five clusters to answer the third question. Of the 195 analyzed domains, 96 are included in only one cluster. Of these, 36 are from cluster C2. However, the cluster with the most documents is cluster C4. This is not surprising since this cluster contains concepts transversal to all RA such as 'Finance Advisory', 'Fintech', 'Innovation', 'RA Implementation', and 'RA Players'. Within this cluster, the most mentioned RA-K family is 'RA implementation', which appears in 48 out of 83 references. Moreover, we observe that clusters C1, C2, and C3 are mostly dealt exclusively. This allows us to conclude that these three clusters have a high degree of specialization. Only eight papers deal simultaneously with clusters C1 and C2, which means that most papers dealing with aspects in which humans are not of great relevance do not deal with topics in which human relationships are important. Cluster C3, devoted to legislation in RA, is also usually dealt with separately. Concerning the authors (fourth question), we have related the 418 authors in our corpus to the 19 families of RA-synonyms. 43.7 % of the authors specialize in a single cluster. Of these, 14.8 % concerned the acceptance or modification of human behavior by interaction with a robot, concepts belonging to the second cluster. 14.4 % were on the implementation of RA, i.e., on topics of the fourth cluster. 10 % analyze topics related to the first cluster, such as the estimation of profitability, the risk, or the portfolio construction. Only 4.5 % of the authors analyze the challenges faced by the regulation or compliance of companies that implement RA as a business. Finally, we highlight that the authors included in the fifth cluster dedicated to the general methodologies applied in the development of RA are also related to aspects of one of the other four clusters. The last two questions refer to the phases of the IAds in which researchers are most interested. From the analyses, it can be concluded that of the two clusters related to the phases of the IAds service, cluster 2 is the one of most significant interest, with 39.5 % of the abstracts and 14.3 % of the authors focusing exclusively on the topics in this cluster. It can, therefore, be deduced that research is more interested in aspects related to the human factor, with the phases that require more direct contact with the client or investor. The automation of client profiling functions (phase 2 of the IAd service) and the client's response to this automation is one of the most relevant research interests.

8. Conclusions

Automated investment management services emerge as an alternative to the traditional investment advice model with the goal of scaling such advice to a larger number of clients at a low cost. To promote investment decisions, it integrates financial technology, portfolio management, and the personal characteristics of investors. In this paper, the Scopus and the WoS bibliographic databases have been merged to expand the number of references to be analyzed and thus obtain more consistent results. From a corpus of 195 RA studies published until May 2022, the current research strives to do a relational analysis between all the relevant topics of RA implementation and the RA research. According to our query, the oldest paper in the WoS is from 2015. However, this article is not in our corpus as it does not meet the condition of having an abstract. Thus, the first article in our corpus was published in 2016. However, we can conclude that research interest in RA is still very recent.

The scope of this study involves several aspects. We elaborate a dictionary of synonyms that we consider to represent all the topics of interest in the study of RA. Two relational analyses, clusters vs abstracts and clusters vs authors, are carried out to conduct an in-depth study of the current situation of RA research. The results of this analysis indicate that the topics of most significant interest are those contained in the cluster *C4-Cross RA business*. 42.5 % of the abstracts and 14.3 % of the authors specifically deal with issues included in this cluster. These percentages indicate that the cross-cutting nature of RA implementation poses important changes in the different phases of the IAd process. *C2-High Human factor* is the second cluster of research interest, with 39.5 % of the abstracts and 14.3 % of authors exclusively focusing on the topics of this cluster. The automation of customer profiling functions (phase 2 of the IAd service) and the customer response to this automation is one of the most relevant research interests. In third place are those topics related to the *C1-Low human factor* cluster. 31.3 % of the abstracts deal with issues related to this cluster, and 10 % of authors research exclusively on them. 'Asset Allocation', 'Risk-performance' and 'Instruments and markets' are the main interests within this cluster. Our study also highlights that 43.7 % of the authors specialize in a single cluster. This implies a high degree of specialization by the authors analyzed. The analysis of the evolution of the research during the study period shows that it initially focused on the problems of RA implementation and development, mainly included in the *C4-Cross RA business*. Once these problems have seemingly been overcome, the research focuses on the more human aspects included in the *C2-High Human factor*. Thus, the artificial interpretation of customers' desires or obtaining the acceptance of RA by investors seem to be the topics of most significant interest in recent years. In addition, we have created an open-source code that can be used by any other researcher interested in conducting a relational analysis on any research topic at any time interval.

In general, the findings in this paper play a key role in the academic trends related to RA research. For new research areas such as RA, a relational analysis can be the most powerful tool to inform academics and professionals about the current state of knowledge in this emerging discipline. This draws a clear guideline for future researchers and practitioners in financial markets.

Like any literature review, this work has several limitations that must be considered. Firstly, on the one hand, the search depends on the sources of information used; in our case, focusing only on Scopus and the WoS. If any relevant literature is not included in these databases, it is left out of the analysis. On the other hand, the search has been limited to documents in English, which may generate a bias in the geographical and cultural representativeness of the literature. Another significant limitation is that it is a static study showing the situation at a given time. RA is an emerging area of research, and the number of papers focusing on it is growing. This leads to the possible exclusion of relevant studies that will become available during the publication process.

Data availability statement

“Corpus Robo-Advisor”, Mendeley Data, V1, https://doi.org/10.17632/zfykpbdrm9.1.

CRediT authorship contribution statement

Mar Arenas-Parra: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Héctor Rico-Pérez:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Raquel Quiroga-Garcia:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table 6
Synonyms associated with *C1-Low human factor*.

Asset Allocation	Instruments Markets	Risk Performance	Q Methods
Asset	Assets	Ar Garch Model	Bootstrap
Asset Allocation	Bond	Financial Risk	Expectation Confirmation Model
Asset Allocation Methods	Bonds	Financial Risk Tolerance	Exponentially Weighted Moving Average
Asset Management	Bonds Commodities	Financial Risks	Financial Data
Black Litterman	Bonds Commodities Exchange	Forecasting	Financial Engineering
Digital Asset Management	Commodity Investment	Market Indicators Of Shares	Financial Market Instability Index
Digital Wealth Management	Copper Investment	Market Prediction	Modeling
Dynamic Portfolios	Emerging Markets	Performance	Momentum
Efficient Portfolios	Energy Market	Performance Analysis	Multiple Mediator Models
Fixed Weight Asset Strategy	Equity	Performance And Risk Analysis	Oriented Fuzzy Number
Goal Based Investing	Equity Fixed	Return	Quality Control
Household Portfolio Choice	Equity Fixed Income	Risk	Quantitative Analysis
Insurance Distribution	Equity Indices	Risk Control	Quantitative Evaluation
Investing	Etf	Risk Factors	Quantitative Methods
Investment	European Insurance Markets	Risk Management	Quantitative Research
Investment Decisions	Exchange Traded Fund	Risk Management	Quantitative Trading
Investment Management	Exchange Traded Funds	Risk Preference	Regression Analysis
Investment Strategy	Financial Assets	Risk_Affinities	Regression Model
Investor Protection	Financial Instruments	Risk_Affinity	Regression Trees
Markowitz	Financial Markets	Risk_Assessment	Semi Definite Relaxation
Markowitz Model	Financial Product	Risk_Aversion	Smart Beta
Markowitz Portfolio Theory	Financial Products	Risk_Level	Space Analysis
Mean Variance Model	Fund Portfolio	Risk_Loving	Structural Equation Modeling
Mean Variance Optimization	Funds	Risk_Measurement	Valuation
Markowitz	Index_Tracking	Risk_Neutral	
Multi Asset	Index_Type	Risks	
Portfolio	Indexes	Sharpe	
Portfolio Allocation	Indices	Sharpe Ratio	
Portfolio Analysis	Investment Product	Stock Prediction	
Portfolio Construction	Markets	Stock Prices	
Portfolio Investments	Mutual Fund	Stock Returns	
Portfolio Management	Mutual Funds	Systemic Risk	
Portfolio Optimization	Pension Builder		
Portfolio Rebalancing	Share Prices		
Portfolio Selection	Stock Bond		
Portfolios	Stock Market		
Robust Optimization	Stocks Bonds		
Securities Portfolio Formation	Stocks Bonds Commodities		
Sparse Portfolio			
Stock Selection			
System Trading			
Worst_Case Optimization			

Table 7
Synonyms associated with *C2-High human factor.*

Behavioral RA Acceptance	Humanization	Decision Making	Customer Interaction
Acceptance	Anthropomorphism	Decision Support	Client
Adoption	Augmented Human Teams	Choice	Client Profiling
Advice Acceptance	Chabot	Choice Architecture	Consumer
Behavior	Chatbots	Consumer Decision Making	Consumers
Behavioral	Human	Consumer Financial Decision Making	Customer
Behavioral Biases	Human_Based	Decision	Customer Relationship Management (CRM)
Behavioral Finance	Human_Machine	Decision Inertia	Customers
Behavioral Portfolio Theory	Humanizing	Decision Strategies	Financial Concerns
Behavioural	Humanizing Technology	Decisions	Investment Knowledge
Behavioural Finance	Humanlike	Financial Decision	Investor_Friendly
Biofeedback	Lack Of Human	Financial Decision Making	Macroprudential Policy
Character Analysis	Verbal	Financial Decision Support	Personal Specific Variable
Confidence		Financial Decision-Making	Personalized
Emotion Classification		Interactive Decision Aid	Profile
Emotion Regulation		Judge_Advisor	Recognition
Financial Behavior		Judgments	Risk Profiling
Flow Theory		Long Life Decision Making	Social Network
Human Vulnerability			Social Trading
Machine Human Interface			Socio_Technical
Overconfidence			Sociological
Perceived			Sociotechnological
Persuasion			Subjective Knowledge
Physiological Arousal			User Centric Design
Propensity			User Control
Psychological Factors			User's Expertise
Technology Acceptance Model			
Trust			
Trust And Expertise			
Trust Transfer Theory			
Uses And Gratifications Theory			
Widely Adopted			

Table 8
Synonyms associated with *C3-Compliance.*

Compliance		
Bank Regulatory Compliance	Legal	Regulation
Cyber Security	Legal Informatics	Regulation Editions
Data Privacy	Legal Risks	Regulation Governing
Disclosure	Legislator	Regulator
Fear Of Investment Fraud	Legitimacy	Regulators
Fiduciary Duty	Legitimating	Regulatory
Fraudulent	Liability In Financial Services	Regulatory Arbitrage
Illegality	Normative	Regulatory Frameworks Set
Insurance Distribution Directive (Idd)	Patent Application	Regulatory Intervention
Judicial	Peer To Peer Insurance	Regulatory Sandbox
Jurisdictions	Personal Information Protection	Regulatory Scrutiny
Korean Law	Policies	Rights
Law	Policymakers	Robolaw
Lawmakers	Power Of Attorney	Self Regulation
Lawsstatutes	Privacy	Structural Assurances
Lawyers	Privacy Rights	Supervisory Control

Table 9
Synonyms associated with *C4-Cross RA business.*

Finance Advisory	Fintech	Innovation	RA Implementation	RA Players
Advice	Financial Technology	Diffusion Of Innovation	Business	Banking
Advice Taking	Fintech Innovation	Disruptive	Business Models	Banks
Defined Contribution Pension Plan	Regtech	Disruptive Innovation	Business Requirements	Blackrock
Egadim	Service Robotics	Financial Innovation	Crowdfunding	Bundesbank
Finance Advisory	Financial Technology (Fintech)	Financial Revolution	Equity Based Crowdfunding	Financial Ecosys
Financial Advice	Fin Tech	Innovation	Financial Network	Financial Firm
Financial Advisers	Fintechs	Innovations	Implementing	Financial Firms
Financial Advisors	Financial Technology Fintech	Innovative Economics	Insurance Intermediaries	Financial Industry

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Table 9 (*continued*)

Finance Advisory	Fintech	Innovation	RA Implementation	RA Players
Financial Advisory Services	Smart Contracts	Inter Organizational Innovation Patterns	Management	Financial Institutions
Financial Education	Modern Financial Technologies	Internet Of Things	Omnichannel (Omni Channel) Sales	Financial Intermediary
Financial Information		Technological	Sandbox	Financial Sector
Financial Management		Technologies	Sustainable Finance	Financial System
Financial Planning		Technology	Task Technology Fit Model	Google
Financial Portfolios		Technology Adoption	Usability	Hedge Fund
Financial Service			Usability Engineering	Ing
Financial Services				Investor
Financial Services Industry				Investors
Generational Wealth Management				Retail Consumer
Global Financial Networks				Retail Investing
Household Finance				Retail Investment
Investment Advice				Retail Investors
Investment Recommendations				
Item Recommendation				
Life Cycle Advising				
Objective Knowledge				
Personal Finance Management				
Personal Financial Planning				
Retirement Planning				
Wealth Management				

Table 10
Synonyms associated with *C5-General Methodologies.*

AI	Algorithms Digitalization	Automated_Investment	Blockchain	Big_Data
Ai Culture	Algo Culture	Automated	Crypto Assets	Big Data Analysis
Artificial Intelligence	Algorithm	Automated Investment Management	Crypto Currencies	Data Science
Artificial Intelligence (Ai)	Algorithm Advice	Automation In Financial Advice	Cryptocurrencies	Data Analysis
Artificial Intelligence Ai	Algorithmic	Dynamic Indicators		Data Clustering
Artificial Intelligent (Ai)	Algorithmic Authority	Group Recommender Systems		Information Search
Artificial Learning	Algorithmic Bias	Intelligent Investment Advisor		Big Data
Bert	Algorithmic Culture	Investment Automation		
Bert Model	Algorithms	Judge Advisor System		
Cluster Analysis	Automation	Online Recommender Systems		
Cognitive Computing	Autonomous Systems	Service Automation		
Collaborative Filtering	Computer			
Computational Intelligence	Digital			
Deep Learning	Digital Divide 2 0			
Digital Twin	Digital Finance			
Experimental Design	Digital Footprint			
Fuzzy Logic	Digital Intermediaries			
Generative	Digital Payments			
Generative_Based	Digital Platform Economy			
Genetic	Digital Transformation			
Hopfield Neural Network	Digitalization			
Incremental Extreme Learning Machine (Ielm)	Expert Systems			
Incremental Extreme Learning Machine Ielm	Genetic Algorithm			
Learning Preferences	Goal Programming			
Machine Intelligence	Information Technology Management			
Machine Learning	Multi Stage Stochastic Programming			
Machine_Learning	Multiple Kernel Learning Mkl			
Multiple Kernel Learning (Mkl)	Programmatic			
Neural Network	Programmer			
Neural Networks	Programmes			
Neural Networks And Their Applications	Programming			
Nlp	Python			
Non Iterative Learning	Smart Contract			
Nudges	Software Architecture			
Nudging	Web Calculators			

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Table 10 (*continued*)

AI	Algorithms Digitalization	Automated_Investment	Blockchain	Big_Data
Reinforcement Learning				
Smart Grid				
Supervised Ai				
Support Vector Machine				
Support Vector Regression				
Task Technology Fit				
Theory Of Network Externalities				

Table 11
Papers database of the study.

	Authors	Title
AB1	Britton B; Atkinson D	An Investigation Into The Significant Impacts Of Automation In Asset Management
AB2	Scherer B	Algorithmic Portfolio Choice; Lessons From Panel Survey Data
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AB5	Godwin A	Brave New World Digital Disclosure Of Financial Products And Services
AB6	Mannaro K; Pinna A; Marchesi M	Cryptotrading Blockchain Oriented Energy Market
AB7	Dorfleitner G; Hornuf L; Schmitt M; Weber M	Fintech In Germany
AB8	Park J; Ryu J; Shin H	How To Manage Portfolio By Robo-advisor
AB9	Faloon M; Scherer B	Individualization Of Robo-advice
AB10	Salampasis D	Leveraging Robo-advisors To Fill The Gap Within The Sri Marketplace
AB11	Lo A	Moores Law Vs Murphys Law In The Financial System: Who's Winning?
AB12	Camarero Aguilera S; López Pascual J	On Asset Managers Hedge Funds And ETFs
AB13	Du Y D	Risk And Management Of Robo-advisor In China Security Market
AB14	Salo M; Haapio H	Robo-advisors And Investors: Enhancing Human-Robot Interaction Through Information Design
AB15	Rogowski W	The Dawn Of Robo-advisors
AB16	Sharf S	The XX Factor
AB17	Xue J; Zhu E; Liu Q; Wang C; Yin J	A Joint Approach To Data Clustering And Robo-advisor
AB18	Bayn P	A Legal Framework For Robo-advisors
AB19	Sa J; Lee K; Cho S; Lee S; Gim G	A Study On The Influence Of Personality Factors On Intention To Use Of Robo-advisor
AB20	Day M; Cheng T; Li J	AI Robo-advisor With Big Data Analytics For Financial Services
AB21	Day M; Lin J; Chen Y	Artificial Intelligence For Conversational Robo-advisor
AB22	Tokic D	Blackrock Robo-advisor 4.0: When Artificial Intelligence Replaces Human Discretion
AB23	Dhar V; Stein R	Complete And Incomplete Fintech Platforms
AB24	Lewis D	Computers May Not Make Mistakes But Many Consumers Do
AB25	Kobets V; Yatsenko V; Mazur A; Zubrii M	Data Analysis Of Private Investment Decision Making Using Tools Of Robo-advisers In Long run Period
AB26	Karakas C; Stamegna C	Defining A Eu-framework For Financial Technology (Fintech): Economic Perspectives And Regulatory Challenges
AB27	Jung D; Dorner V; Weinhardt C; Pusmaz H	Designing A Robo-advisor For Risk-averse Low budget Consumers
AB28	Chen K	Financial Innovation And Technology Firms: A Smart New World With Machines
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AB31	Chen K; Sergi B	How Can Fintech Impact Russias Development
AB32	Beltramini E	Human Vulnerability And Robo-advisory. An Application Of Coeckelberghs Vulnerability To The Machine-Human Interface
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AB34	Snihovyi O; Ivanov O; Kobets V	Implementation Of Robo-advisors Using Neural Networks For Different Risk Attitude Investment Decisions
AB35	Schwinn R; Teo E	Inclusion Or Exclusion Trends In Robo-advisory For Financial Investment Services
AB36	Xue J; Liu Q; Li M; Liu X; Ye Y; Wang S; Yin J	Incremental Multiple Kernel Extreme Learning Machine And Its Application In Robo-advisors
AB37	Lee K; Kwon H; Lim J	Legal Consideration On The Use Of Artificial Intelligence Technology And Self regulation In Financial Sector Focused On Robo-advisors
AB38	Liu C	Legal Risks And The Countermeasures Of Developing Intelligent Investment Advisor In China
AB39	Jung D; Erdfelder E; Glaser F	Nudged To Win: Designing Robo-advisory To Overcome Decision Inertia
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AB43	Beketov M; Lehmann K; Wittke M	Robo Advisors: Quantitative Methods Inside The Robots
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AB47	Lewis D	The Perils Of Overconfidence: Why Many Consumers Fail To Seek Advice When They Really Should

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AB49	Rühr A; Streich D; Berger B; Hess T	A Classification Of Decision Automation And Delegation In Digital Investment Management Systems
AB50	Guo F; Cheng X; Zhang Y	A Conceptual Model Of Trust Influencing Factors In Robo-advisor Products: A Qualitative Study
AB51	Gu C; Hsieh H; Wu C; Chang R; Ho J	A Fund Selection Robo-advisor With Deep learning Driven Market Prediction
AB52	Chen L; Liu K; Wang Y; Zhang H	A Portfolio Selection Model For Robo-advisor
AB53	Wang P; Liu C; Yang Y; Huang S	A Robo-advisor Design Using Multiobjective Rank nets With Gated Neural Network Structure
AB54	Engin Z; Treleaven P	Algorithmic Government Automating Public Services And Supporting Civil Servants In Using Data Science Technologies
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AB57	Belanche D; Casal L; Flavin C	Artificial Intelligence In Fintech: Understanding Robo-advisors Adoption Among Customers
AB58	Mendez-Suarez M; Garcia-Fernandez F; Gallardo F	Artificial Intelligence Modelling Framework For Financial Automated Advising In The Copper Market
AB59	Haberly D; Macdonald-Korth D; Urban M; Wjcik D	Asset Management As A Digital Platform Industry: A Global Financial Network Perspective
AB60	Rühr A; Berger B; Hess T	Can I Control My Robo-advisor? Tradeoffs In Automation And User Control In Digital Investment Management. Completed Research
AB61	Kliman R; Arinze B	Cognitive Computing Impacts On Financial Advice In Wealth Management
AB62	Bruckes M; Westmattelmann D; Oldeweme A; Schewe G	Determinants And Barriers Of Adopting Robo-advisory Services
AB63	Cheng X; Guo F; Chen J; Li K; Zhang Y; Gao P	Exploring The Trust Influencing Mechanism Of Robo-advisor Service: A Mixed Method Approach
AB64	Misina S	Financial Web Calculators
AB65	Brummer C; Yadav Y	Fintech And The Innovation Trilemma
AB66	Tauchert C; Mesbah N	Following The Robot? Investigating Users' Utilization Of Advice From Robo-advisors
AB67	Chen M; Wu Q; Yang B	How Valuable Is Fintech Innovation
AB68	Snihovyi O; Kobets V; Ivanov O	Implementation Of Robo-advisor Services For Different Risk Attitude Investment Decisions Using Machine Learning Techniques
AB69	Mosteanu N	International Financial Markets Under Artificial Intelligence Influence
AB70	Riley E; Schild M	Living Or Dying In The Mashup Of American Financial Services: Literate Does Not Mean Competent
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AB95	Agarwal S; Chua Y	Fintech And Household Finance: A Review Of The Empirical Literature
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	Authors	Title
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AB106	Guo L	Regulating Investment Robo-advisors In China: Problems And Prospects
AB107	Liu R	Research On Financial Risks Of Robo-advisor Platforms
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AB109	Cuzzola P	Robo-advice, Artificial Intelligence And Responsibility: The Regulatory Framework Between Present Scenarios And Future Perspectives
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AB111	Tan G	Robo-advisors And The Financialization Of Lay Investors
AB112	Baek S; Lee K; Uctum M; Oh S	Robo-advisors Machine Learning In Trend-following ETF Investments
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AB114	North R	Sensitivity Validation Of A Fuzzy System For Asset Allocation
AB115	Bi Q; Tang J; Van F B; Nelson J; Beal I; Ray C; Ossola A	Software Architecture For Machine Learning In Personal Financial Planning
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AB117	Ruishi J; Shujun Y	The Development Status And Legal Supervision Of Robo-advisors Under Financial Technology
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AB119	Kabulova J; Stankeviien J	Valuation Of Fintech Innovation Based On Patent Applications
AB120	Torno A; Schildmann S	What Do Robo-advisors Recommend? An Analysis Of Portfolio Structure Performance And Risk
AB121	Brandl B; Hornuf L	Where Did Fintechs Come From And Where Do They Go? The Transformation Of The Financial Industry In Germany After Digitalization
AB122	Harrison J; Samaddar S	Who Is Better At Investment Decisions: Man Or Machine?
AB123	Loureno C; Dellaert B; Donkers B	Whose Algorithm Says So: The Relationships Between Type Of Firm, Perceptions Of Trust And Expertise, And The Acceptance Of Financial Robo-advice
AB124	Luo X; Feng K; Fang X	A Framework For Robo-advisor Based On Knowledge Fusion
AB125	He W; Lau R	A Hybrid Deep Learning Model For Emotion Detection In Emotion-sensitive Robo-advisors
AB126	Yin C; Perchet R; Soup F	A Practical Guide To Robust Portfolio Optimization
AB127	Paul L; Sadath L	A Systematic Analysis On Fintech And Its Applications
AB128	Seiler V; Fanenbruck K	Acceptance Of Digital Investment Solutions: The Case Of Robo Advisory In Germany
AB129	Guo H; Polak P	After The Collision Of Crisis And Opportunity To Redefining The Artificial Intelligence In Finance: The New Intelligent Finance Era
AB130	Canoz I	An Exploration Into The Posture Of Robo-advisor Globally
AB131	Atwal G; Bryson D	Antecedents Of Intention To Adopt Artificial Intelligence Services By Consumers In Personal Financial Investing
AB132	Deng B; Chau M	Anthropomorphized Financial Robo-advisors And Investment Advice-taking Behavior
AB133	Bhatia A; Chandani A; Atiq R; Mehta M; Divekar R	Artificial Intelligence In Financial Services: A Qualitative Research To Discover Robo-advisory Services
AB134	Rasiwala F; Kohl B	Artificial Intelligence In Fintech: Understanding Stakeholders Perception On Innovation Disruption And Transformation In Finance
AB135	Helms N; Hlscher R; Nelde M	Automated Investment Management: Comparing The Design And Performance Of International Robo-managers
AB136	Duc K N D; Sermpinis G; Stasinakis C	Big Data, Artificial Intelligence And Machine Learning: A Transformative Symbiosis In Favour Of Financial Technology
AB137	Au C; Klingenberger L; Svoboda M; Frre E	Business Model Of Sustainable Robo-advisors: Empirical Insights For Practical Implementation
AB138	Chen X; Ye S; Huang C	Cluster-based Mutual Fund Classification And Price Prediction Using Machine Learning For Robo-advisors
AB139	Potdar A; Pande M	Comprehensive Analysis Of Machine Learning Algorithms Used In Robo-advisory Services
AB140	Hildebrand C; Bergner A	Conversational Robo Advisors As Surrogates Of Trust: Onboarding Experience, Firm Perception, And Consumer Financial Decision Making
AB141	Tubadji A; Denney T; Webber D	Cultural Relativity In Consumers Rates Of Adoption Of Artificial Intelligence
AB142	Dai W	Development And Supervision Of Robo-advisors Under Digital Financial Inclusion In Complex Systems
AB143	Gerlach J; Lutz J	Digital Financial Advice Solutions Evidence On Factors Affecting The Future Usage Intention And The Moderating Effect Of Experience
AB144	Bhatia A; Chandani A; Divekar R; Mehta M; Vijay N	Digital Innovation In Wealth Management Landscape: The Moderating Role Of Robo Advisors In Behavioural Biases And Investment Decision-making
AB145	Bai Z	Does Robo-advisory Help Reduce The Likelihood Of Carrying A Credit Card Debt? Evidence From An Instrumental Variable Approach
AB146	Chandani A; Bhatia A	Education Sector And Robo Advisory: Does Specialization Of Study Affect Awareness?
AB147	Mayenberger D	Explainable Artificial Intelligence: A Global Fast Approach
AB148	Xue R; Gepp A; Oneill T; Stern S; Vanstone B	Financial Literacy And Financial Strategies: The Mediating Role Of Financial Concerns
AB149	Lu B; Hao S; Pinedo M; Xu Y	Frontiers In Service Science: Fintech Operations - An Overview Of Recent Developments And Future Research Directions
AB150	Ge R; Zheng Z; Tian X; Liao L	Human-Robot Interaction: When Investors Adjust The Usage Of Robo-advisors In Peer-to-Peer Lending

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	Authors	Title
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AB152	Gerhana Y; Umam M; Atmadja A	Implementation Of The Markowitz Method In The Robo-advisor Application For Best Investment Selection
AB153	Wang X; Butt A; Zhang Q; Ahmad H; Shafique M	Intention To Use AI-powered Financial Investment Robo-advisors In The M-banking Sector Of Pakistan
AB154	Oehler A; Horn M; Wendt S	Investor Characteristics And Their Impact On The Decision To Use A Robo-advisor
AB155	Slaughter K; Chen D	Is Knowledge Power Or Ignorance Bliss? Delegate And Educate In Robo-advising: A Proposed Study Of The Human-agentic IS Artifacts Dyad's Shared Domain Knowledge
AB156	Fernández Ss	Islamic Fintech
AB157	Darskuviene V; Lisauskiene N	Linking The Robo-advisors Phenomenon And Behavioural Biases In Investment Management - An Interdisciplinary Literature Review And Research Agenda
AB158	Streich D	Risk Preference Elicitation And Financial Advice Taking
AB159	Ringe W; Ruof C	Robo Advice Legal And Regulatory Challenges
AB160	Tao R; Su C; Xiao Y; Dai K; Khalid F	Robo Advisors, Algorithmic Trading And Investment Management: Wonders Of Fourth Industrial Revolution In Financial Markets
AB161	Wang H; Yu S	Robo-advising Enhancing Investment With Inverse Optimization And Deep Reinforcement Learning
AB162	Alsabah H; Capponi A; Ruiz L O; Stern M	Robo-advising Learning Investors Risk Preferences Via Portfolio Choices
AB163	So M	Robo-advising Risk Profiling Through Content Analysis For Sustainable Development In The Hong Kong Financial Market
AB164	Dong Z; Zhu M; Xu F	Robo-advisor Using Closed-form Solutions For Investors' Risk Preferences
AB165	Leow E; Nguyen B; Chua M	Robo-advisor Using Genetic Algorithm And Bert Sentiments From Tweets For Hybrid Portfolio Optimization
AB166	Grealish A; Kolm P	Robo-advisors Today And Tomorrow: Investment Advice Is Just An App Away
AB167	Bach P	Robo-advisory An Opportunity For Innovation In Sharia-compliant Markets
AB168	Chandani A; Sriharshitha S; Bhatia A; Atiq R; Mehta M	Robo-advisory Services In India: A Study To Analyze Awareness And Perception Of Millennials
AB169	Mehrotra A; Menon S	Second Round Of Fintech Trends And Challenges
AB170	Waliszewski K; Warchlewska A	Selected Countries Of Eastern And Central Europe In The Face Of Challenges Of Modern Financial Technologies (Based On The Example Of Robo-advice)
AB171	Hodge F; Mendoza K; Sinha R	The Effect Of Humanizing Robo-advisors On Investor Judgments
AB172	Buchanan B; Wright D	The Impact Of Machine Learning On UK Financial Services
AB173	Pal A; Sharma S; Gupta K	The Role Of Analytics And Robo-advisory In Investors' Financial Decisions And Risk Management: Review Of Literature Postglobal Financial Crisis
AB174	Kristjanpoller W; Michell K; Minutolo P	Trading Support System For Portfolio Construction Using Wisdom Of Artificial Crowds And Evolutionary Computation
AB175	Wu M; Gao Q	Understanding The Acceptance Of Robo-advisors: Towards A Hierarchical Model Integrated Product Features And User Perceptions
AB176	Deo S; Sontakke N	Usability, User Comprehension, And Perceptions Of Explanations For Complex Decision Support Systems In Finance: A Robo-advisory Use Case
AB177	Jiang T	Using Machine Learning To Analyze Merger Activity
AB178	Zhang L; Pentina I; Fan Y	Who Do You Choose? Comparing Perceptions Of Human Vs Robo-advisor In The Context Of Financial Services
AB179	Cheng Y	Will Robo-advisors Continue? Roles Of Task technology Fit, Network Externalities, Gratifications And Flow Experience In Facilitating Continuance Intention
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AB181	Shan S; Umar M; Mirza N	Can Robo Advisors Expedite Carbon Transitions? Evidence From Automated Funds
AB182	Anshari M; Almunawar M; Masri M	Digital Twin: Financial Technology's Next Frontier Of Robo-advisor
AB183	Chhatwani M	Does Robo-advisory Increase Retirement Worry? A Causal Explanation
AB184	Tsai S; Chen C	Exploring The Innovation Diffusion Of Big Data Robo-advisor
AB185	Fritz-Morgenthal S; Hein B; Papenbrock J	Financial Risk Management And Explainable Trustworthy Responsible AI
AB186	Zheng K; Cheong J; Jafarian M	Intention To Adopt Robo-advisors Among Malaysian Retail Investors: Using An Extended Version Of Tam Model
AB187	Flavian C; Pérez-Rueda A; Belanche D; Casal L	Intention To Use Analytical Artificial Intelligence (AI) In Services. The Effect Of Technology Readiness And Awareness
AB188	Manrai R; Gupta K	Investor's Perceptions On Artificial Intelligence (AI) Technology Adoption In Investment Services In India
AB189	Piehlmaier D	Overconfidence And The Adoption Of Robo-advice: Why Overconfident Investors Drive The Expansion Of Automated Financial Advice
AB190	Liu X; Yuan X; Zhang R; Ye N	Risk Assessment And Regulation Algorithm For Financial Technology Platforms In Smart City
AB191	Caballero-Fernández R; Cortez K; Ceballos-Hornero D	Robo Advisors Vs Value Investing Strategies: A Fuzzy Jensen's Alpha Assessment
AB192	Wexler M; Oberlander J	Robo-advice (RA): Implications For The Sociology Of The Professions
AB193	Alekseenko A	Shall Regulators Introduce Special Rules For Robo Advising Services?
AB194	Huang R; Wang C; Zhang O	The Development And Regulation Of Robo-advisors In Hong Kong: Empirical And Comparative Perspectives
AB195	Von W B; Kremmel D; Jger B	The Impact Of Lay Beliefs About AI On Adoption Of Algorithmic Advice

References

[1] H.K. Çalışkan, Technological change and economic growth, procedia – soc, Behav. Sci. 195 (2015) 649–654, https://doi.org/10.1016/j.sbspro.2015.06.174.
[2] D. Jung, D. Erdfelder, F. Glaser, Nudged to win: designing robo-advisory to overcome decision inertia, Research-in-Progress Papers 19 (2018).
[3] M. Faloon, B. Scherer, Individualization of robo-advice, J. Wealth Manag. 20 (1) (2017) 30–36, https://doi.org/10.3905/jwm.2017.20.1.030.
[4] Statista, Statistical portal, robo-advisors-worldwide, Retrieved from, https://www.statista.com/outlook/dmo/fintech/digital-investment/robo-advisors/worldwide?currency=usd, 2024. (Accessed 5 April 2024).
[5] K. Hakala. Robo-advisors as a form of artificial intelligence in private customers' investment advisory servicesBachelor's thesis, 2019, pp. 1–34. https://urn.fi/URN:NBN:fi:aalto-201907214391.
[6] D. Jung, F. Glaser, W. Köpplin, Robo-advisory: opportunities and risks for the future of financial advisory, in: Advances in Consulting Research: Recent Findings and Practical Cases, 2019, pp. 405–427.
[7] M. Levine, J. Mackey, Humans versus robots, CPA J. 87 (5) (2017) 6–7.
[8] A. Oehler, Matthias Horn, Does ChatGPT provide better advice than robo-advisors? Financ. Res. Lett. 60 (2024) 104898 https://doi.org/10.1016/j.frl.2023.104898.
[9] F. D'Acunto, A.G. Rossi, Robo-advising. CESifo Working Papers Series, 2020, p. 8225.
[10] A. Torno, D.R. Metzler, V. Torno, Robo-What?, Robo-Why?, Robo-How?-A Systematic Literature Review of Robo-Advice, PACIS, 2021, p. 92.
[11] H. Rico-Pérez, M. Arenas-Parra, R. Quiroga-Garcia, Scientific development of Robo-advisor: a bibliometric analysis, Rev. Econ. Finance 20 (2022) 776–786, https://doi.org/10.55365/1923.x2022.20.87.
[12] G. Cardillo, H. Chiappini, Robo-advisors: a systematic literature review, Financ. Res. Lett. 62 (2024) 105119, https://doi.org/10.1016/j.frl.2024.105119.
[13] M. Beketov, K. Lehmann, M. Wittke, Robo advisors: quantitative methods inside the robots, J. Asset Manag. 19 (6) (2018) 363–370, https://doi.org/10.1057/s41260-018-0092-9.
[14] B. Ankita, C. Arti, C. Jagriti, Robo advisory and its potential in addressing the behavioral biases of investors - a qualitative study in Indian context, J Behav Exp Finance 25 (2020) 100281, https://doi.org/10.1016/j.jbef.2020.100281.
[15] G. Vincent, V. Laknidhi, P. Klein, R. Gera, Robo-advisors: capitalizing on a growing opportunity, J Res Robo Advisor Tech (2015) 2. Retrieved from, https://www2.deloitte.com/content/dam/Deloitte/us/Documents/strategy/uscons-robo-advisors.pdf. (Accessed 14 June 2022).
[16] D. Jung, V. Dorner, F. Glaser, S. Morana, Robo-advisory: digitalization and automation of financial advisory, Bus. Inf. Syst. Eng. (2018) 81–86, https://doi.org/10.1007/s12599-018-0521-9.
[17] L. Brenner, T. Meyll, Robo-advisors a substitute for human financial advice, J. Behav. Exp. Finance 25 (2020) 100275, https://doi.org/10.1016/j.jbef.2020.100275.
[18] V. Tiberius, R. Gojowy, M. Dabi'c, Forecasting the future of robo advisor. a Three-stage Delphi study on economic, technological and societal implications, Technol. Forecast. Soc. Change 182 (2022), https://doi.org/10.1016/j.techfore.2022.121824.
[19] W.F. Sharpe, Investors and Markets: Portfolio Choices. Asset Prices. And Investment Advice, Chapter Eight, Princeton University Press, 2006. ProQuest Ebook Central, https://ebookcentral.proquest.com/lib/bibliotecaie-ebooks/detail.action?docID=485801.
[20] Wipro, Future of robo-advisors in investment and wealth management, Retrieved from, https://www.wipro.com/content/dam/nexus/en/industries/securities-and-capital-markets/latest-thinking/future-of-robo-advisors-in-investment-and-wealth-management.pdf, 2020. (Accessed 5 May 2023).
[21] A. Aghaei Chadegani, H. Salehi, M. Yunus, H. Farhadi, M. Fooladi, M. Farhadi, N. Ale Ebrahim, A comparison between two main academic literature collections: Web of science and Scopus databases, Asian Soc. Sci. 9 (2013) 18–26, https://doi.org/10.5539/ass.v9n5p18.
[22] J.A. Moral-Muñoz, E. Herrera-Viedma, A. Santisteban-Espejo, M.J. Cobo, Software tools for conducting bibliometric analysis in science: an up-to-date review, Prof Inf (2020) 1–20, https://doi.org/10.3145/epi.2020.ene.03.
[23] J. Chew, Robo-advice the battle for millennials' money, Fortune 172 (8) (2015) 156–162.
[24] B.L. Britton, D.G. Atkinson, An investigation into the significant impacts of automation in asset management, in: Economic and Social Development: Book of Proceedings, 2016, p. 393.
[25] M. Aria, C. Cuccurullo, Bibliometrix: an R-tool for comprehensive science mapping analysis, J. Informetr. 11 (4) (2017) 959–975, https://doi.org/10.1016/j.joi.2017.08.007.
[26] I. Feinerer, K. Hornik, D. Meyer, Text mining infrastructure in R, J. Stat, Soft 25 (5) (2008) 1–54, https://doi.org/10.18637/jss.v025.i05.
[27] T. Galili, A. O'Callaghan, J. Sidi, C. Sievert, Heatmaply: an R package for creating interactive cluster heatmaps for online publishing, Bioinformatics 34 (9) (2017) 1600–1602, https://doi.org/10.1093/bioinformatics/btx657.
[28] C.F. Dormann, B. Gruber, J. Fruend, Introducing the bipartite package: analysing ecological networks, R. News 8 (2) (2008) 8–11.
[29] I. Romero-Pérez, A. Pulido-Rojano, Aplicaciones del método de análisis de palabras asociadas (Co-Words), in: J.H. Ávila Toscano (Ed.), Cienciometría y bibliometría. El estudio de la producción científica: Métodos, enfoques y aplicaciones en el estudio de las Ciencias Sociales, Corporación Universitaria Reformada, 2018, pp. 147–194 (Coord).
[30] M. Callon, J.P. Courtial, F. Laville, Co-word analysis as a tool for describing the network of interactions between basic and technological research: the case of polymer chemistry, Scientometrics 22 (1991) 155–205, https://doi.org/10.1007/BF02019280.
[31] A. de la Hoz-Correa, F. Munoz-Leiva, M. Bakucz, Past themes and future trends in medical tourism research: a co-word, Tour Manag (2018) 200–211, https://doi.org/10.1016/j.tourman.2017.10.001.
[32] C. Vallaster, S. Kraus, J.M. Merigó-Lindahl, A. Nielsen, Ethics and entrepreneurship: a bibliometric study and literature review, J. Bus. Res. 99 (2019) 226–237, https://doi.org/10.1016/j.jbusres.2019.02.050.
[33] E. Abad-Segura, M.D. González-Zamar, Global research trends in financial transactions, Mathematics 8 (2020) 614, https://doi.org/10.3390/math8040614.
[34] F. D'Acunto, N. Prabhala, A.G. Rossi, The promises and pitfalls of robo-advising, Rev. Financ. Stud. 32 (5) (2019) 1983–2020, https://doi.org/10.1093/rfs/hhz014.
[35] M. Ji, Are robots good fiduciaries? Regulating robo-advisors under the investment advisers act of 1940, Colum. L. Rev. 117 (2017) 1543.
[36] Z. Engin, P. Treleaven, Algorithmic government automating public services and supporting civil servants in using data science technologies, Comput. J. 62 (3) (2019) 448–460, https://doi.org/10.1093/comjnl/bxy082.
[37] X. Liu, X. Yuan, R. Zhang, N. Ye, Risk assessment and regulation algorithm for financial technology platforms in smart city, Comput. Intell. Neurosci. (2022), https://doi.org/10.1155/2022/9903364.
[38] P. Gomber, R. Kauffman, C. Parker, B. Weber, On the Fintech revolution: interpreting the forces of innovation, disruption, and transformation in financial services, J. Manag. Inf. Syst. 35 (1) (2018) 220–265, https://doi.org/10.1080/07421222.2018.1440766.
[39] T. Baker, B. Dellaert, Regulating robo advice across the financial services industry, Iowa Law Rev. 103 (2) (2018) 713–750, https://doi.org/10.2139/ssrn.2932189.
[40] M.A. Chen, Q. Wu, B. Yang, How valuable is FinTech innovation? Rev. Financ. Stud. 32 (5) (2019) 2062–2106, https://doi.org/10.1093/rfs/hhy130.
[41] C.F. Dormann, A method for detecting modules in quantitative bipartite networks: the QuanBiMo algorithm, Methods Ecol. Evol. (2014) 90–98, https://doi.org/10.1111/2041-210X.12139.
[42] A. Oehler, M. Horn, S. Wendt, Investor characteristics and their impact on the decision to use a robo-advisor, J. Financial Serv. Res. 62 (2022) 91–125, https://doi.org/10.1007/s10693-021-00367-8.
[43] M.L. Bartlett, J.S. McCarley, Human interaction with automated aids: implications for robo-advisors, Financial Planning Review 2 (3–4) (2019) e1059.