Robo-Advisors in Wealth Management: A Bibliometric Study of Research Evolution

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Article Info	ABSTRACT
	Robo-advisors have emerged as a transformative force in wealth management, leveraging artificial intelligence (AI) and machine learning to provide automated financial advisory services. This study conducts a bibliometric analysis of research on robo-advisors using data exclusively from the Scopus database and analyzed through VOSviewer. The findings reveal that research in this field has evolved from foundational discussions on fintech and artificial intelligence to advanced themes such as machine learning, decentralized finance, and algorithmic transparency. The keyword analysis highlights "wealth management," "fintech," and "machine learning" as central themes, while the co-authorship network indicates strong interdisciplinary collaboration among researchers. Additionally, the study identifies key regulatory and ethical challenges, including data privacy, fiduciary responsibility, and algorithmic bias, which require further investigation. The discussion explores the technological advancements, investor behavior, and regulatory landscape shaping the future of robo-advisory services. This research contributes to the growing academic discourse by mapping the intellectual structure of robo-advisor studies and suggesting future research directions, particularly in the areas of explainable AI (XAI), blockchain integration, and personalized financial advisory models.

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1. INTRODUCTION

The integration of artificial intelligence (AI) and financial technology (FinTech) has revolutionized the wealth management industry, leading to the emergence of robo-advisors. Robo-advisors are automated digital platforms that provide financial planning services with minimal human supervision, leveraging algorithms and big data to offer investment recommendations [1]. These AI-driven platforms have gained popularity due to their efficiency, cost-effectiveness, and accessibility, particularly among retail investors seeking low-cost wealth management solutions [2]. As financial markets become increasingly complex, robo-advisors are expected to play a more significant role in assisting both individual and institutional investors in portfolio management and decision-making.

Academic interest in robo-advisors has grown significantly, with researchers

examining their implications for investor behavior, financial literacy, regulatory challenges, and the overall efficiency of wealth management services [3]. The body of literature on robo-advisors spans multiple disciplines, including finance, technology, behavioral economics, and regulatory studies, reflecting the multifaceted impact of these digital tools. The increasing adoption of robo-advisory services, coupled with ongoing advancements in AI and machine learning, has fueled the need for a structured analysis of existing research trends and gaps in this field.

Bibliometric analysis has emerged as an essential method for systematically reviewing and mapping the intellectual landscape of a research domain. By analyzing citation networks, co-authorship patterns, and keyword trends, bibliometric studies provide valuable insights into the evolution of academic discourse on specific topics [4]. In the context of robo-advisors, bibliometric research can help identify key themes, influential publications, and emerging research directions. This methodological approach enables scholars to understand how the field has evolved over time and how it may develop in the future.

Despite the growing body of literature on robo-advisors, there is still a lack of comprehensive bibliometric studies that analyze the development and trajectory of research in this domain. While previous studies have explored various aspects of robo-advisors, such as their technological framework, adoption barriers, and ethical considerations, an overarching bibliometric synthesis remains limited [5]. Addressing this gap can help academics and practitioners gain a deeper understanding of the theoretical foundations and empirical trends shaping the field. Given the rapid technological advancements and regulatory shifts affecting the wealth management industry, it is crucial to evaluate the research evolution of robo-advisors. A bibliometric study can provide a structured overview of scholarly contributions, highlight influential studies, and reveal potential research opportunities. By tracing the academic development of robo-advisors, this study aims to contribute to a more informed discourse on the role of AI in financial advisory services.

The academic literature on robo-advisors is expanding rapidly, yet there is no comprehensive bibliometric study that systematically examines the evolution of research in this field. Without such an analysis, it is challenging to assess the key research themes, identify influential authors and institutions, and determine the direction of future studies. The lack of a structured overview hampers the ability of scholars and practitioners to navigate the growing body of knowledge and leverage past research for innovation and policy-making in wealth management. This study aims to conduct a bibliometric analysis of research on robo-advisors in wealth management, mapping the intellectual structure, research trends, and thematic evolution of the field.

2. LITERATURE REVIEW

2.1 The Emergence and Evolution of Robo-Advisors

Robo-advisors represent a significant technological advancement in financial services, leveraging artificial intelligence (AI), big data, and algorithmic trading to automate investment decisions and wealth management [6]. The concept of automated financial advising has existed for decades, but the launch of early platforms such as Betterment and Wealthfront in the late 2000s marked the beginning of widespread adoption [7]. These digital platforms initially focused on portfolio allocation and rebalancing based on modern portfolio theory (MPT) but have since evolved to incorporate more sophisticated AI models, including machine learning and predictive analytics [8]. Recent studies highlight that robo-advisors provide several benefits compared to traditional human advisors, such as lower costs, greater accessibility, and elimination of emotional biases in investment decisions [9]. However, concerns regarding algorithmic transparency, lack of personalization, and

limited adaptability to volatile market conditions persist [10]. Additionally, while early robo-advisors catered primarily to retail investors, many financial institutions now integrate robo-advisory services into their business models to complement human financial advisors, leading to a hybrid advisory approach [11].

2.2 Technological Foundations of Robo-Advisors

The backbone of robo-advisors lies in AI-driven algorithms that analyze large datasets to provide investment recommendations [12]. These algorithms rely on various computational techniques, including rule-based systems, machine learning, and deep learning [13]. One of the most widely used methodologies in robo-advisory systems is MPT, developed by [14], which focuses on optimizing asset allocation by balancing risk and return. However, advancements in financial computing have led to the incorporation of more complex models, such as reinforcement learning and neural networks, to improve predictive accuracy [15]. Another critical aspect of robo-advisors is natural language processing (NLP), which enhances user interactions through chatbots and voice recognition systems [16]. These NLP capabilities allow robo-advisors to simulate financial consultations, improving the overall user experience. Additionally, sentiment analysis, a subset of AI, has been increasingly integrated into robo-advisory services to gauge investor sentiment from financial news and social media, thus enabling dynamic portfolio adjustments [17].

2.3 Behavioral Factors and Investor Adoption of Robo-Advisors

Investor acceptance of robo-advisors has been a widely studied topic, with research focusing on behavioral finance theories such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) [18]. These models suggest that perceived usefulness, ease of use, trust, and financial literacy are significant determinants of robo-advisor adoption [19]. Empirical studies have found that younger, tech-savvy investors are more likely to adopt robo-advisory services due to their familiarity with digital platforms and lower preference for traditional financial advisors [20]. Additionally, individuals with higher risk tolerance and lower financial literacy tend to rely more on robo-advisors, as they seek guidance in navigating investment decisions [21]. However, trust remains a critical factor, with concerns over the reliability and transparency of AI-driven recommendations acting as barriers to adoption [22]. Moreover, studies have explored the role of robo-advisors in mitigating common behavioral biases, such as loss aversion and overconfidence [23]. Unlike human advisors, robo-advisors make objective decisions based on data-driven insights, reducing emotional influences on investment choices. Nevertheless, there is still skepticism regarding whether robo-advisors can effectively replace human intuition and personalized financial guidance [24].

2.4 The Role of Regulation in the Development of Robo-Advisors

As robo-advisors gain prominence, regulatory bodies worldwide have introduced guidelines to ensure consumer protection, financial stability, and ethical AI deployment [25]. The regulatory landscape varies across jurisdictions, with the U.S. Securities and Exchange Commission (SEC), the European Securities and Markets Authority (ESMA), and the Monetary Authority of Singapore (MAS) implementing frameworks to govern automated investment advisory services [26]. A critical regulatory concern is fiduciary responsibility—ensuring that robo-advisors act in the best interest of their clients [27]. Traditional financial advisors are subject to fiduciary standards, but whether robo-advisors should be held to the same requirements

remains a contentious issue [28]. Additionally, data privacy and cybersecurity regulations play a vital role in safeguarding client information, with laws such as the General Data Protection Regulation (GDPR) in Europe imposing stringent requirements on financial technology firms [29]. Scholars argue that regulatory sandboxes—controlled environments where fintech innovations can be tested under regulatory supervision—offer a promising approach to fostering innovation while maintaining consumer protection [30]. These regulatory initiatives enable financial firms to experiment with robo-advisory models before full-scale deployment, ensuring compliance with legal frameworks while minimizing risks.

2.5 *Performance and Efficiency of Robo-Advisors*

The effectiveness of robo-advisors in portfolio management has been widely debated. Some studies suggest that robo-advisors outperform traditional investment strategies due to their data-driven decision-making capabilities [7]. Research comparing the returns of portfolios managed by robo-advisors and human advisors has found mixed results, with some studies indicating comparable or superior performance from robo-advisors, while others highlight limitations in adapting to market fluctuations [8]. An essential factor influencing robo-advisor performance is their ability to rebalance portfolios dynamically in response to market conditions [11]. Machine learning techniques have improved robo-advisors' ability to predict market trends and optimize asset allocations, yet challenges remain in handling extreme market events, such as financial crises. Additionally, studies have explored the cost efficiency of robo-advisors, emphasizing their lower management fees compared to traditional wealth managers, making them an attractive option for cost-conscious investors [2].

3. METHOD

This study employs a bibliometric analysis to investigate the research evolution of robo-advisors in wealth management using academic publications exclusively retrieved from the Scopus database. The data collection process involves defining search queries with relevant keywords such as "robo-advisors," "wealth management," "financial technology," and "automated investment", ensuring the inclusion of peer-reviewed journal articles and conference proceedings. The retrieved data will undergo cleaning and refinement, removing duplicate or irrelevant records to ensure accuracy. The analysis will be conducted using VOSviewer, a bibliometric software tool, to map citation networks, co-authorship patterns, and keyword co-occurrence, identifying influential publications, research clusters, and thematic trends.

4. RESULT AND DISCUSSION

4.1 Results

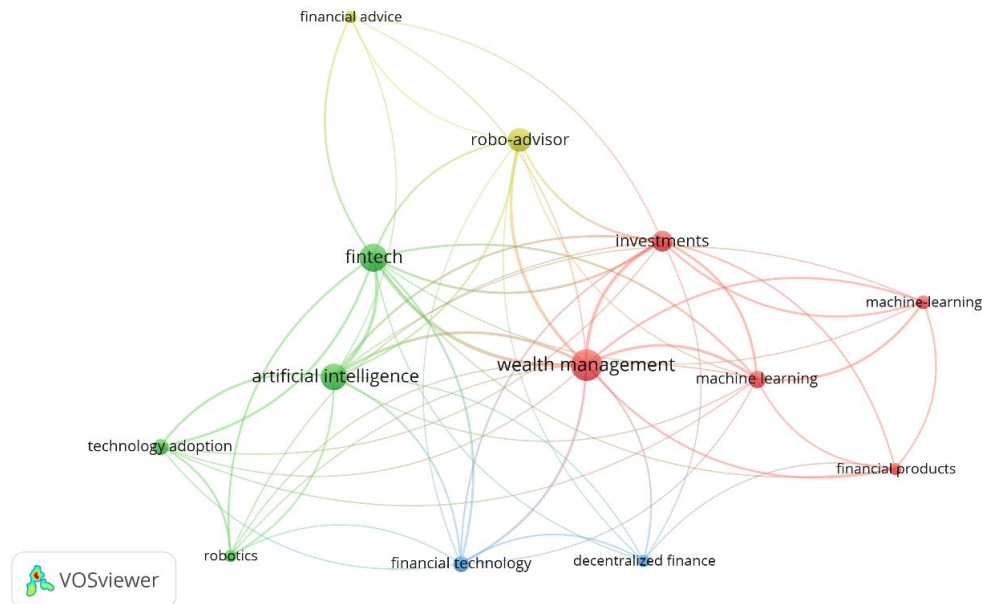#### a. Keyword Co-Occurrence Network Visualization

Figure 1. Network Visualization
Source: Data Analysis, 2025

The VOSviewer visualization represents a bibliometric network analysis of the research landscape surrounding robo-advisors in wealth management. The nodes in the network signify key terms extracted from academic literature, while the edges connecting them indicate their co-occurrence in publications. The network is divided into distinct clusters, each represented by different colors, which highlight thematic groupings within the field. Larger nodes, such as "wealth management" and "fintech," suggest that these terms appear frequently and serve as central topics in the existing research on robo-advisors. The red cluster is centered around "wealth management," "investments," and "machine learning." This suggests that a significant portion of research focuses on the intersection of investment strategies and machine learning technologies in wealth management. The presence of "financial products" in this cluster indicates that studies often examine how AI-driven robo-advisors help investors manage diverse financial assets efficiently. The strong connections between "machine learning" and "wealth management" emphasize the role of predictive analytics and automated decision-making in modern investment advisory services.

The green cluster revolves around "fintech," "artificial intelligence," and "technology adoption." This highlights the growing academic interest in the technological foundations of robo-advisors, particularly how AI-driven financial services are adopted by investors and financial institutions. The inclusion of "robotics" and "technology adoption" in this cluster suggests that automation and AI-driven decision-making processes are

key areas of research. This cluster likely includes studies exploring the challenges and opportunities of integrating AI in financial services, including issues of trust, regulatory compliance, and technological limitations. The yellow cluster, featuring "robo-advisor" and "financial advice," underscores the focus on the role of robo-advisors in providing financial guidance. This thematic grouping suggests research on how robo-advisors are perceived compared to traditional human advisors, particularly in terms of trust, user experience, and financial literacy. The links between "robo-advisor" and "fintech" indicate that robo-advisory services are seen as an integral part of the fintech ecosystem, transforming the way financial advice is delivered to both retail and institutional investors. The blue cluster, which includes "financial technology" and "decentralized finance," highlights the connection between robo-advisors and emerging financial innovations such as blockchain and decentralized finance (DeFi). This suggests that some research is exploring the potential of robo-advisors in DeFi applications, possibly focusing on how smart contracts and decentralized platforms could further automate and democratize investment management. The presence of "financial technology" reinforces the idea that robo-advisors are part of a broader digital transformation in financial services.
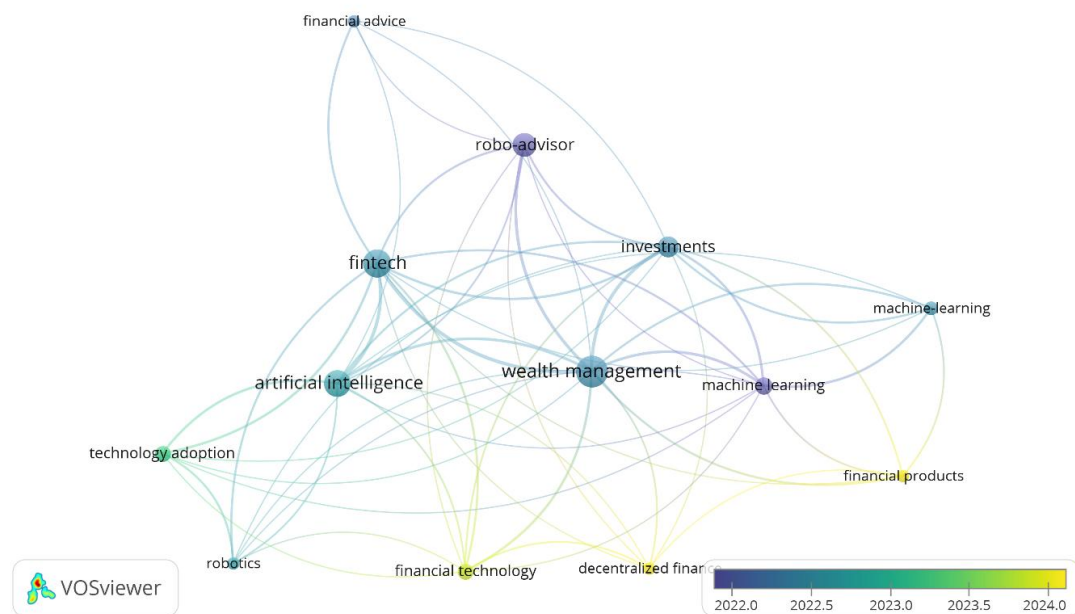

Figure 2. Overlay Visualization
Source: Data Analysis, 2025

The visualization above is a bibliometric overlay map depicting the evolution of research related to robo-advisors in wealth management over time. The color gradient, ranging from blue to yellow, represents the average publication year of studies associated with each term, as indicated by the legend at the bottom right. Dark blue nodes signify older research contributions (around 2022), while yellow nodes indicate more recent publications (closer to 2024). The structure of the map highlights key themes such as wealth management, fintech, artificial

intelligence, investments, and machine learning, with their interconnections showing co-occurrence in academic literature. The visualization reveals that earlier research (2022-2023) focused heavily on foundational topics, such as "wealth management," "fintech," and "artificial intelligence," which appear in shades of blue. This suggests that initial studies centered on understanding the role of AI and fintech in wealth management, exploring how automated systems could enhance financial advisory services. Similarly, concepts like "technology adoption" and "robotics" are also linked to earlier studies,

reflecting early discussions on the integration of AI-driven automation in finance. More recent studies (2023-2024), indicated by yellow-green nodes, highlight emerging topics such as "financial products," "decentralized finance," and "financial technology." This shift suggests growing interest in how robo-advisors interact with decentralized financial ecosystems and new AI-driven financial products. The appearance of "machine learning" in a lighter shade indicates that ongoing research is delving deeper into advanced AI applications in financial decision-making.
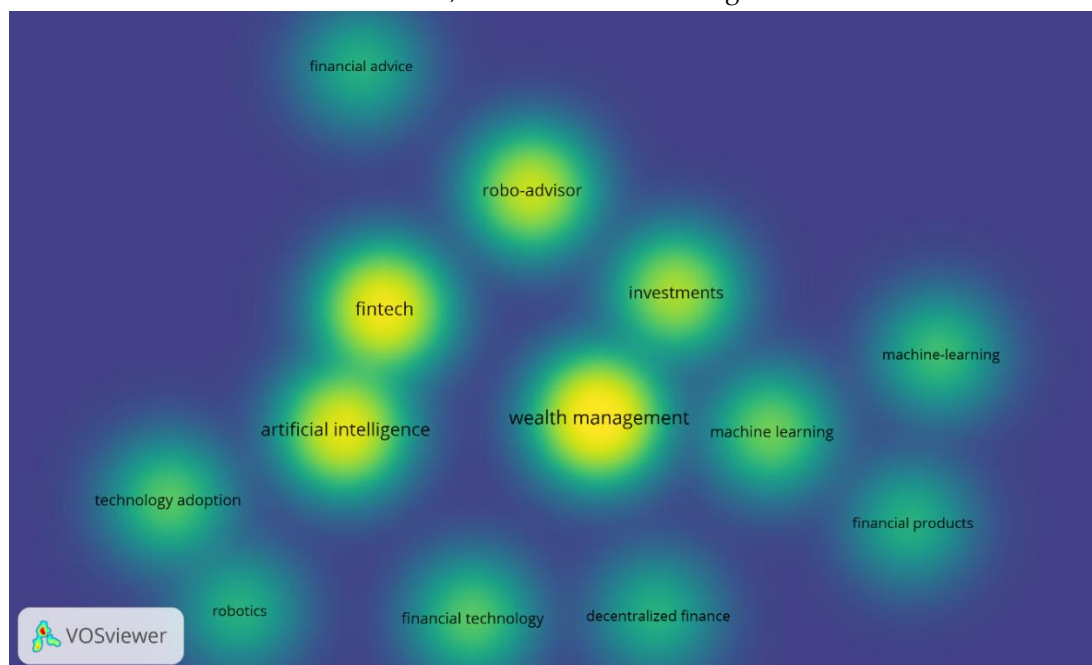

Figure 3. Density Visualization
Source: Data Analysis, 2025

The VOSviewer density visualization in the image provides insights into the intensity of research activity related to robo-advisors in wealth management. The color gradient represents the concentration of publications associated with specific keywords, where bright yellow areas indicate high research density, while green and blue regions reflect moderate to lower research

activity. The most prominent research themes are centered around "wealth management," "fintech," and "artificial intelligence," suggesting that these topics are the focal points of scholarly discussions. Other notable high-density terms include "robo-advisor" and "investments," reflecting their central role in financial technology and AI-driven wealth management research. Lower-density

terms such as "financial technology," "decentralized finance," and "financial products" indicate emerging but still developing research areas. The presence of "machine learning" and "technology adoption" suggests that scholars are increasingly exploring the role of AI-driven decision-making and the adoption of digital advisory services. The spread of research across various subfields highlights an interdisciplinary approach, integrating finance, artificial intelligence, and investment management. This density map underscores the need for further exploration in less-explored areas like decentralized finance and financial technology, which are likely to gain more attention in future research.
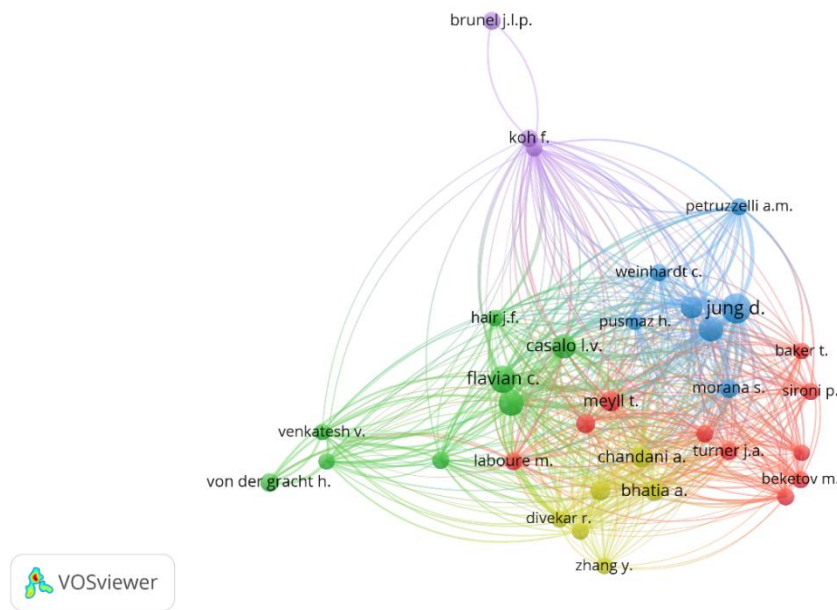
b. Co-Authorship Network

Figure 4. Co-Authorship Visualization
Source: Data Analysis, 2025

The VOSviewer co-authorship network visualization in the image represents the collaboration patterns among researchers studying robo-advisors in wealth management. Each node represents an author, and the edges connecting them indicate co-authorship relationships, with different colors signifying distinct collaborative groups. Larger nodes represent highly influential or frequently cited authors, while closely connected nodes suggest strong research collaborations. The network is divided into multiple clusters, with notable researchers such as Jung D., Casalo L.V., Flavian C., and Sironi P. forming central hubs, indicating their significant contributions to the field. The green and red clusters show dense connectivity, suggesting well-established collaboration networks, while the purple cluster (e.g., Koh F. and Brunel J.L.P.) appears more isolated, implying limited interaction with other research groups.

c. **Citation Analysis**

Table 1. Most Cited Article

Citations	Author and Year	Title
406	[31]	Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers
320	[32]	In the Horns of the Dilemma: Socioemotional Wealth, Financial Wealth, and Acquisitions in Family Firms
152	[33]	Financial Advisors and Shareholder Wealth Gains in Corporate Takeovers
136	[34]	Check-in at the Robo-desk: Effects of automated social presence on social cognition and service implications
120	[35]	Conversational robo advisors as surrogates of trust: onboarding experience, firm perception, and consumer financial decision making
115	[36]	CEO Risk-Taking and Socioemotional Wealth: The Behavioral Agency Model, Family Control, and CEO Option Wealth
112	[24]	FinTech Innovation
94	[37]	Robo advisors, algorithmic trading and investment management: Wonders of fourth industrial revolution in financial markets
90	[38]	Robo-advisors: A substitute for human financial advice?
87	[39]	Beyond Markowitz

Source: Scopus, 2025

4.2 Discussion

a. **Research Trends and Thematic Evolution in Robo-Advisory Studies**

The bibliometric analysis reveals that robo-advisors in wealth management have gained significant academic attention in recent years, with research themes evolving from foundational discussions on fintech and artificial intelligence to more specialized topics such as machine learning, decentralized finance, and financial product innovation. The keyword analysis indicates that early research focused on technology adoption and AI integration in financial services, aligning with broader fintech advancements. However, more recent studies have shifted toward the efficacy of robo-advisors in investment management, behavioral finance implications, and regulatory considerations. The network visualization of keywords further confirms the interdisciplinary nature of robo-advisory research, where finance, artificial intelligence, behavioral economics, and regulatory studies intersect. The strong connections between terms such as "machine learning" and "wealth management" suggest that scholars are particularly interested in the role of AI-driven decision-making in portfolio management. Similarly, the emergence of "decentralized finance" and "financial technology" in newer studies highlights the growing intersection between blockchain-based financial services and automated investment management, a potential area for future research.

b. **Key Contributors and Collaborative Networks in Robo-Advisory Research**

The co-authorship network analysis reveals distinct clusters of scholars contributing to robo-advisory research. Authors such as Jung D., Casalo L.V., Flavian C., and Sironi P. appear as central figures in the field, indicating their significant contributions and influence on academic discourse. Their frequent collaborations suggest that the study of robo-advisors benefits from cross-institutional and interdisciplinary research efforts, particularly between

finance, technology, and behavioral economics. Interestingly, certain research groups appear more isolated, such as the cluster led by Koh F. and Brunel J.L.P., indicating limited collaboration with the broader academic community. This suggests potential opportunities for enhanced networking and knowledge sharing, especially between scholars focusing on different aspects of robo-advisors, such as technological development, financial regulations, and behavioral finance. Increased collaboration across these domains could lead to more comprehensive insights into the challenges and opportunities presented by robo-advisory services.

c. **The Role of AI and Machine Learning in Robo-Advisory Services**

The bibliometric analysis highlights machine learning as a key driver of innovation in robo-advisory services. Early robo-advisors primarily relied on rule-based algorithms and modern portfolio theory (MPT) for asset allocation. However, recent advancements in AI have introduced more sophisticated predictive analytics, deep learning, and reinforcement learning models that improve the accuracy and efficiency of robo-advisory platforms. One of the critical benefits of AI-driven robo-advisors is their ability to process vast amounts of financial data, detect market patterns, and provide personalized investment strategies. However, this technological advancement also presents challenges related to algorithmic bias, transparency, and adaptability to extreme market conditions. While machine learning enhances robo-advisors' predictive capabilities, there are still concerns about their ability to respond effectively during financial crises or black swan events, where historical data may not be a reliable predictor of

future trends. Addressing these concerns requires further research into explainable AI (XAI) and hybrid advisory models, where human expertise complements algorithmic decision-making.

d. **Investor Behavior and Adoption of Robo-Advisors**

The literature highlights investor behavior and trust as crucial factors influencing the adoption of robo-advisory services. Research suggests that younger, tech-savvy investors are more likely to embrace digital investment platforms due to their cost-effectiveness, convenience, and accessibility. However, older and high-net-worth investors often exhibit skepticism toward fully automated advisory services, preferring human financial advisors for personalized guidance and emotional reassurance. Trust in robo-advisors is influenced by several behavioral finance factors, including:

1. Perceived Transparency: Investors are more likely to use robo-advisors if they understand how the algorithm makes investment decisions. Lack of transparency in AI-driven recommendations remains a significant barrier to adoption.

2. Risk Perception: While some investors appreciate the data-driven, unbiased nature of robo-advisors, others perceive algorithmic decision-making as rigid and unable to respond to market volatility effectively.

3. Financial Literacy: Individuals with lower financial literacy tend to rely more on robo-advisors for investment decisions, while those with higher financial knowledge often prefer hybrid models that combine AI with human expertise.

Given these behavioral considerations, financial institutions are increasingly adopting hybrid

robo-advisory models, where AI handles routine portfolio management, while human advisors provide strategic financial planning and client engagement. Future research should explore how robo-advisors can enhance investor confidence through transparency measures, user education, and personalized financial recommendations.

e. **Regulatory and Ethical Considerations in Robo-Advisory Services**

The regulatory landscape surrounding robo-advisors varies across jurisdictions, with financial authorities implementing different levels of oversight to ensure consumer protection, financial stability, and ethical AI deployment. The U.S. Securities and Exchange Commission (SEC), the European Securities and Markets Authority (ESMA), and the Monetary Authority of Singapore (MAS) have introduced guidelines to regulate automated investment platforms, focusing on fiduciary responsibility, data privacy, and cybersecurity compliance. Key regulatory challenges include:

1. Fiduciary Responsibility: Should robo-advisors be held to the same fiduciary standards as human financial advisors? The debate continues over whether automated financial services can act in the best interests of investors without human oversight.
2. Data Privacy and Security: Given that robo-advisors rely on large-scale data analytics, concerns over personal data security, algorithmic transparency, and compliance with regulations such as GDPR are growing.
3. Algorithmic Bias and Fairness: Machine learning models may inadvertently introduce biases

based on historical data, leading to unintended discriminatory practices in investment recommendations. Ensuring fairness in AI-driven financial services is a pressing ethical concern.

To address these challenges, regulators are exploring "regulatory sandboxes"—controlled environments where fintech innovations can be tested under supervision before large-scale deployment. Future research should examine how policy frameworks can balance financial innovation with investor protection while promoting ethical AI use in robo-advisory services.

f. **Future Research Directions and Emerging Trends**

Based on the bibliometric findings, several emerging research directions can be identified:

1. Integration of Blockchain and Decentralized Finance (DeFi): The increasing intersection between robo-advisors and DeFi platforms presents an exciting research opportunity. How can smart contracts and blockchain technology improve the transparency and efficiency of robo-advisory services?
2. Explainable AI (XAI) in Financial Decision-Making: Enhancing the interpretability and transparency of robo-advisory algorithms is crucial for building investor trust. Research on XAI techniques can help develop more user-friendly, accountable AI systems in financial services.
3. Behavioral Finance and Personalization in Robo-Advisory Services: Future studies should explore how AI can tailor investment strategies to individual investor behaviors and financial goals, improving

adoption rates among diverse investor demographics.

4. Comparative Studies of Regulatory Frameworks: Given the diverse regulatory approaches across regions, comparative analyses can provide insights into best practices for overseeing robo-advisory services while fostering financial innovation.

5. CONCLUSION

The bibliometric analysis of robo-advisors in wealth management highlights the multidisciplinary nature of research in this field, encompassing financial technology, AI-driven decision-making, investor behavior, and regulatory considerations. The study reveals that research has evolved from fundamental fintech discussions to more advanced themes such as machine learning, decentralized finance, and ethical AI deployment. The co-authorship network visualization underscores the importance of collaborative research, with key scholars shaping the discourse on robo-advisory services. As robo-advisors continue to reshape the wealth management industry, future research should focus on enhancing transparency, addressing regulatory challenges, and exploring the integration of emerging financial technologies. By bridging technology, finance, and behavioral economics, scholars and practitioners can develop more efficient, ethical, and investor-friendly robo-advisory solutions for the future.

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