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Implementing artificial intelligence empowered financial advisory services: A literature review and critical research agenda

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ABSTRACT

Robo-advisors, also known as robo-advisory services, significantly reshape customer service in financial advisory industries, transforming retail investor markets by substituting human financial advisory experts with artificial intelligence empowered services. However, existing literature remains scattered across disciplines, with theories on financial customer service predominantly focused on Internet banking, neglecting artificial intelligence empowered interactions. Thus, service providers need a framework for implementing robo-advisors in frontline service and researchers require an advanced agenda to stimulate future research. Through a systematic, interdisciplinary literature review based on Belanche et al.'s service robot framework, this article contextualizes service robot theories into financial advisory services, synthesizing knowledge on artificial intelligence empowered customer service. We contribute to literature on service robots by contextualizing, refining, and extending the original framework by Belanche et al. and by developing a research agenda with critical perspectives. Moreover, the study yields practical and theoretical insights into artificial intelligence empowered financial advisory services.

1. Introduction

1.1. Research background: Service robots in financial advisory services

Artificial Intelligence (AI)-empowered financial advisory services (i.e.: robo-advisors) have been investigated and discussed by researchers from different aspects and disciplines, constituting a wide range of knowledge regarding their emergence, evolvement, implementation, design, and application. However, existing knowledge regarding robo-advisors is fragmented, calling for a structured and integrative framework for researchers and service providers.

Due to the formidable computational capabilities of AI, customer service providers employ AI for the analysis and assimilation of user data, yielding diverse benefits within frontline customer services (Kaplan & Haenlein, 2019). In contrast to other digital technologies, AI possesses the ability to tailor services to individual customers and to make predictions through intricate algorithms without human intervention. Furthermore, AI's interface can communicate, interact, and provide customer service, all while operating autonomously. This interactive, adaptive, and autonomous interface, is referred to as a service robot (Wirtz et al., 2018).

The deployment of service robots extends across multiple service sectors, from healthcare (Holland et al., 2021; Roy et al., 2000) to hotels (Choi et al., 2020; Pinillos et al., 2016), tourism (McCartney & McCartney, 2020), and domestic environments (Breuer et al., 2012; Forlizzi & DiSalvo, 2006). These robots can have physical or virtual appearances, manifesting through user interfaces. Examples are Amazon's Alexa, a virtual voice-controlled assistant often embedded in smart speakers, and Pepper, a social and interactive humanoid robot developed by SoftBank Robotics. Such robots may adopt human-like features (e.g., Sophia, a humanoid robot developed by Hanson Robotics) or non-humanoid features (e.g., cleaning robots) (Belk et al., 2023; Lu et al., 2020; Wirtz et al., 2018). Moreover, service robots possess the capacity for social engagement with customers, creating emotional value in service encounters (Čaić et al., 2019).

Recently, the utilization and integration of service robots within the financial service sector have gained notable attention, driven by their rapid proliferation in the retail investment market, especially during the COVID-19 pandemic (Ben-David & Sade, 2020; Gan et al., 2021). In terms of design, physical-appearance service robots have not yet been implemented in the financial advisory sector, but robots in use today do encompass anthropomorphized features. For instance, they adopt

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features such as avatars with human names and capabilities that mimic those of human financial advisors. Current research underscores the importance of AI and robotic automation as pivotal trends in the financial sector (Met et al., 2020; Thekkethil et al., 2021). Projections suggest a fully automated financial sector in the forthcoming years (Rao & Verweij, 2017).

Compared to customer service research in other domains, the use of artificial intelligence in financial advisory services and the existing knowledge of customers using them remain underdeveloped. Therefore, this study focuses on service robots specially designed for and utilized within financial advisory services.

A robo-advisor, also referred to as robo-advisory service, is a type of service robot based on an AI-empowered autonomous information system. This system incorporates interactive interfaces designed to offer financial advisory services, requiring minimal to no human intervention (Day et al., 2018; Jung, Dorner, Glaser, et al., 2018). Unlike other technological innovations in financial services such as ATMs, digital wallets, and internet banks, robo-advisors possess the capability to replace human financial advisors who are frontline employees in delivering advisory services and directly interacting with customers. Financial advisory services, provided by retail banks or other FinTech firms, are customer-facing services that are aimed at providing customers with professional advice on financial planning, investments, and asset management. Unlike customers in various other service sectors, those engaging with financial advisory services tend to maintain prolonged and deeply involved commitments, such as long-term investments, while also facing the risk of potential asset loss if their chosen financial products underperform (Belanche et al., 2019). Researchers and practitioners in financial advisory services face new challenges regarding the potential consequences of replacing human interaction with a robot in service encounters (Chia, 2019; Dhar, 2016; Iacurci, 2022; Tokic, 2018). Such new challenges and he exploration of robo-advisor technology may lead to several unintended consequences for customers or service providers, with wider unintended implications for the finance sector more broadly.

1.2. Research gaps and aims

Numerous articles regarding robo-advisory services have been published across various journals and conference proceedings in recent years. Amidst this literature, three distinct gaps come to light. Firstly, these studies are scattered across research disciplines each with its own focal points. This necessitates an interdisciplinary analysis and the development of an integrative framework to reorganize and synthesize existing evidence into new knowledge.

Secondly, the extensive knowledge and theories on human-AI interaction remain unapplied in the context of financial services (e.g.: Belanche et al., 2020; Robinson et al., 2020). This absence makes it challenging for service providers to make managerial decisions regarding robo-advisors. Most customer service research within financial services focuses on Internet banking or other digital service formats, or is concentrated on financial performance (Chauhan et al., 2022; Klink et al., 2020; Mbama & Ezepue, 2018). The frontline customer service, encompassing direct communication and customer interaction, remains difficult to understand in financial service encounters. As previously highlighted, robo-advisory services in the frontline are complicated, with many intertwined factors that can jointly affect customers' decision-making. Besides functional expectations, such as the robo-advisor's performance in optimizing investment returns, customers also need emotional and social connections when interacting with robo-advisors (Hildebrand & Bergner, 2021; Hohenberger et al., 2019).

Thirdly, the existing robo-advisor literature shows a degree of redundancy in terms of topics and methods, including technology acceptance theories and behavioral finance theories. Despite their empirical contributions, these studies lack the novelty necessary to propel robo-advisory technologies or robo-advisory services. The robo-advisor literature has evolved from the embryonic stage, and it is time to critically evaluate existing studies and stimulate new research agendas for further research.

This article aims to systematically assess and synthesize the existing evidence and knowledge of service robots in financial advisory services, particularly frontline customer service encounters.

To identify and emphasize robo-advisory service implementation research, we adopt a robust framework from a highly cited paper published by Belanche et al. in 2020 (Fig. 1). This framework will be introduced in the research background section in detail. Based on the framework, we conduct a systematic literature review and thematic analysis that contextualizes this framework within financial advisory service.

With this, we aim to explore and extend the framework established by Belanche et al. (2020). Our extended framework serves the purpose of synthesizing scattered literature, thereby equipping service providers with a holistic comprehension of the various roles played by different stakeholders in robo-advisor customer service. This, in turn, aids them in decision-making in practice. Moreover, we aim to address the research gaps in robo-advisor research by proposing a critical research agenda.

Therefore, this study makes two contributions. Firstly, it contributes to knowledge of robo-advisor services in financial advisory contexts. Secondly, it contributes to literature on service robots by contextualizing, refining, and extending the original framework by Belanche et al. and by developing a research agenda with critical perspectives.

This article begins with a theoretical background. We introduce concepts related to financial advisory services and the framework by Belanche et al. and offer a comparative analysis between our study and previous literature reviews on robo-advisors to underscore the novelty and contributions. Then, the methodology section outlines the motivation and process of literature searching, selecting, screening, and analysing. This is followed by the findings section. Lastly, the discussion and conclusion sections present a research agenda, our contributions, and the implications for research and practice.

2. Theoretical background

2.1. Financial advisory service in the age of AI

Over the past few decades, researchers within the realm of financial

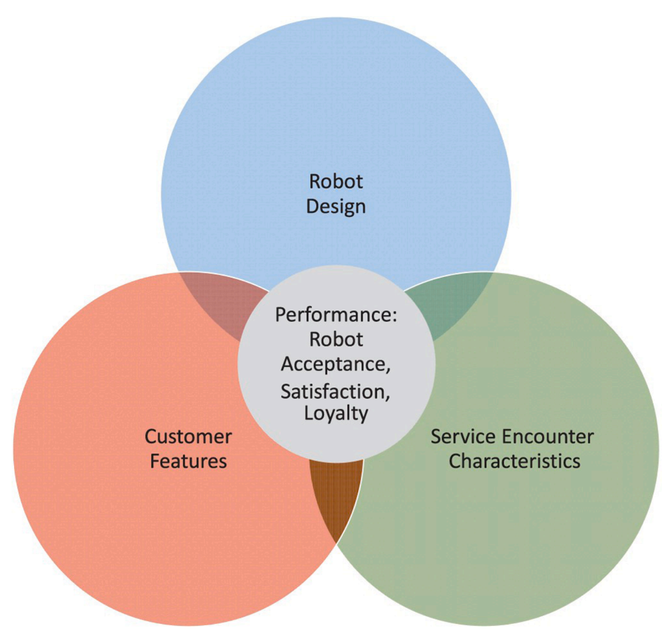

Fig. 1. Belanche et al.'s framework on service robot implementation (Belanche et al., 2020).

services have shared the notion that customer-trust theories and the principles of service-dominant logic drive the maximization of the value provided by customer services (Morgan & Hunt, 1994). In line with these theories, the customer-bank relationship built and maintained by human advisors has influenced customer perceptions, thereby establishing itself as the cornerstone of the financial advice sector (Söderberg, 2013).

However, state-of-the-art technology and dynamic marketing, which construct disruptive innovations and intense competition, call for a transformation of frontline customer service in financial advisory services from human-labor service to AI-empowered service (Baulkaran & Jain, 2023; Chia, 2019; Fulk et al., 2018). Nowadays, the interface of robo-advisors has emerged as one of the predominant channels through which customers interact and communicate with service providers. Notably, the customer experience and perception fostered through this interface is a constituent part of the overall service encounter.

Collectively, these factors shape customer experience and behaviors encountered at the service frontline. Therefore, the customer service encounter becomes a natural focus area of AI-empowered financial advisory services. This concept of service encounters encompasses a wide spectrum, spanning from a customer's initial indirect or direct interaction with a service provider, product, or service (Meyer & Schwager, 2007; Walker, 1995). For example, customers may come across service advertisements, receive recommendations from acquaintances, browse websites, and engage with dedicated mobile applications.

In the era dominated by AI, customers increasingly rely on self-navigation and make decisions based on interactions with autonomous service systems and interfaces. Within the financial advisory sector, the management of customer relationships and trust presents challenges. New factors, including customers' attitudes towards algorithms (Ganbold et al., 2021), competence in using self-service systems (Deo & Sontakke, 2021a), and comprehension of intricate financial terms and domain knowledge (Salo & Haapio, 2017), now exert influence over the customer experience. Furthermore, adherence to regulations, laws, and ethical considerations are crucial in establishing high-quality customer service. Moreover, this imposes new requirements on customer protection.

Given the paradigm shifts introduced by AI-empowered financial advisory services, both service providers and researchers find themselves in need of an advanced framework. This framework should channel heightened attention towards the frontline service and the holistic customer experience.

Therefore, this literature review article will emphasize the customer service encounter, touching upon multiple factors integral to service design and implementation. This approach aims to foster a holistic understanding of service robots within the context of financial advisory services.

2.2. Belanche et al.'s service robot implementation framework

We have opted to employ the framework devised by Belanche et al. (2020) to analyze literature concerning the implementation of service robots (Fig. 1). Our decision to adopt this framework as the "baseline framework" stems from its inclusivity of service robots across diverse industries, as well as its clarification of terminology and concepts commonly employed in prior research. This, in turn, provides a holistic understanding of service robots, effectively equipping service providers with the insights required for their successful integration within target customer segments. Specifically, the framework centers around three pivotal themes — robot design, customer features and service encounter characteristics — which collectively establish the prerequisites for service robot implementation. The framework's detailed presentation can be found in the analysis within the findings section.

While comprehensive, this framework does exhibit two limitations pertinent to the scope of this article. Initially, its subthemes maintain a generality stemming from the authors' overarching analysis of service robots, potentially lacking the precise contextualization necessary for financial advisory services. Secondly, the interrelations between these fundamental themes remain underexplored, for example, how can design affect customers with various features in service encounters?

Therefore, the intent of our study is to refine and expand this framework. We aim to achieve this by redefining the primary sub-themes to align with the nuances of financial advisory services. Furthermore, our work introduces novel sub-themes under each key theme, collectively elevating the framework's applicability. In particular, our work extends the framework through the following strategies:

1. Contextualizing the three core themes: We adopt and contextualize the core themes — robot design, customer features, and service encounter characteristics — through an analysis of the context of financial advisory services, explaining some theoretical propositions in the original framework.
2. Refining the three core themes: Through analysis within financial advisory services and a comparison of findings with the original framework, the three core themes of the original framework are refined.
3. Extending the framework with new themes: Building upon our thematic analysis, we introduce additional themes to the framework. Particularly, we introduce "Ethics, Regulations, and Laws" as an overarching and integral theme within the framework.

2.3. Comparison to other robo-advisor review papers

This section undertakes a comparison between our review paper and the existing robo-advisor review papers, encompassing aspects such as methodologies and implications (Table 1). The existing three review articles, being recently published, have significantly contributed to the understanding of robo-advisors. Through this comparison, our literature review demonstrates advancements across various dimensions.

Primary, our review emphasizes findings that unveil interrelations between design, customers and service encounters. This distinctive perspective can give service providers and policymakers pragmatic insights for effective customer service implementation. Moreover, it fosters understandings of the interrelations between the three main themes — robot design, customer features, and service encounter characteristics. For example, the inclusion of "anthropomorphism", as an element under the theme "robot design" offers an impact on customer features due to its effect on customers' risk preferences.

In addition to our distinct analytical perspective, our review paper employs a systematic literature review methodology that yields a transparent and rigorous corpus of peer-reviewed articles. This compilation not only showcases the research achievements but also serves as a guide for future research by identifying trends and gaps related to robo-advisory services.

Furthermore, our approach integrates perspectives from various disciplines, strengthening comprehension of the transformative advancements within customer services across diverse domains. These include areas such as financial services, behavioral finance, information systems, design science, as well as legal frameworks and regulations. This interdisciplinary and holistic stance facilitates a comprehensive understanding of the evolving landscape.

3. Method

3.1. Systematic literature review

This review article seeks to attain a comprehensive and interdisciplinary understanding of the latest research concerning robo-advisors and their application in the frontline customer service within financial advisory. To achieve this, we conducted a systematic literature review covering an interdisciplinary body of literature from marketing,

Table 1
A comparison of existing review papers with this paper.

Existing review papers				Our review paper
Title & Authors	Nr. of papers reviewed	Research approach	Research focus	How and what it extends beyond the existing reviews
Artificial intelligence in customer-facing financial services: a systematic literature review and agenda for future research (Hentzen et al., 2022)	90	A systematic literature review in business studies	1. An overview of contexts and research focused on existing robo-advisor literature in financial services.	1. An interdisciplinary perspective, including literature on robo-advisors from financial service, information systems, design science, law, and regulation. Aims for a comprehensive understanding of existing robo-advisor studies and potential synergies.
			2. Uses TCCM (Theory, Context, Characteristics and Methodology) framework and focuses on the methods and theories in the literature on robo-advisors.	2. Adopts the service robot implementation framework (Belanche et al., 2020). Focuses on the results/findings related to frontline customer service.
			3. Aims to identify gaps and proposes an agenda for future research.	3. Aims to provide a managerial reference for service providers and a critical agenda for future research.
Linking the Robo-advisors Phenomenon and Behavioral Biases in Investment Management: An Interdisciplinary Literature Review and Research Agenda (Lisauskiene & Darskuviene, 2021)	7	An interdisciplinary literature review, but not systematic	1. The relationship between the robo-advisor phenomenon and behavioral bias of investors.	1. Not only does the discussion encompass customer features associated with behavioral biases (such as risk and overconfidence), but it also incorporates viewpoints from various related disciplines.
Robo-What?, Robo-Why?, Robo-How? – A Systematic Literature Review of Robo-Advice (Torno & Metzler, 2021)	42	A systematic literature review in information systems research field	1. Descriptive statistics of literature on robo-advisors within information system studies, focusing on research approaches and regional focus.	1. The study not only provides descriptive data but also contributes to a profound analysis of essential concepts, variables, and interrelations within the realm of robo-advisor literature. Additionally, it offers insights into the positioning of authors within various domains.
			2. The three –main themes framework (robo-advisor users, service, and competitions) is a taxonomy based on categorizing existing knowledge.	2. It presents a comprehensive framework that not only elucidates the dynamic relationships and variables inherent in robo-advisor services but also provides practical implications.
			3. Focuses on actors rather than their interrelations.	3. Focuses on both overarching concepts and their interrelations.

business management, behavioral finance, asset management, human–computer interaction, information systems, and computer science. These research fields are pertinent to this article's purpose, as they encompass most of the robo-advisor-related literature that informs our research inquiries.

A systematic literature review serves the purpose of synthesizing existing knowledge and collective evidence ("what we know"), thereby enabling the critical evaluation of extant research while identifying potential areas for future research ("what should we know") (Paul et al., 2021; Snyder, 2019; Walsh & Downe, 2005). The research process follows a theory-driven approach, characterized as a "framework-based review", renowned for its informative, insightful, and impactful attributes (Paul et al., 2021). This article adopts the "service robot implementation framework" developed by Belanche et al. as a theoretical guideline for literature search, selection, and analysis. Consequently, through analysis, this article refines and extends the framework.

These methods offer several advantages: (1) explicit research aims and questions, (2) a transparent and reproducible research protocol, (3) a thematic analysis of existing research based on a reliable theoretical framework, (4) a new conceptual framework based on an extension of the existing theoretical framework, (5) an in-depth and critical examination of the extant literature, and (6) insightful propositions for further research.

This method effectively addresses gaps in previous robo-advisor literature reviews (Table 1). Firstly, we include articles derived from multiple research domains, rather than limiting ourselves to a singular research field. This inclusion of diverse perspectives is exemplified by sources such as Hentzen et al. (2022) and Torno & Metzler (2021). Also, by conducting a systematic and theory-driven literature review centered specifically on the implementation of robo-advisor services, we fill gaps left by previous review articles (Hentzen et al., 2022; Lisauskiene & Darskuviene, 2021; Torno & Metzler, 2021).

The research process comprises four phases: (1) defining research aims and questions, (2) establishing a protocol for literature search, including determining the study's scope, selecting search engines and databases, and identifying keywords, (3) conducting a rigorous screening of the corpus by establishing inclusion and exclusion criteria, and (4) analyzing and synthesizing the literature during the analysis process.

3.2. Search terms

We began by testing various search terms in different literature databases. We ultimately selected Scopus as the source, as it provided results that aligned with the aim of this article and covered a broader range of journals than other databases, as also substantiated by prior research (Falagas et al., 2008; Mongeon & Paul-Hus, 2016). Relevant search terms were chosen based on the existing body of literature. The specific combinations of search terms are detailed in Table 2. Following Belanche et al. (2020), the first keyword selection (Group 1) encompasses three themes: (1) robo-advisors, (2) customers, and (3) financial advisory service. Synonyms related to these themes were also considered as they appear in current literature. Another search term (Group 2) was added to supplement the first search, as some articles in business studies only use terms like "Robo-advice" and "Robo-advisory" to refer to AI-empowered financial advisory services. The two bodies of literature are complementary yet independent of each other. The searches were conducted on titles, abstracts, and keywords.

Table 2
Search terms.

Three themes	Group 1	Group 2
robo-advisor	("robo*" OR "automat*" OR "algorithm*" OR "machine*" OR "AI" OR "artificial intelligence")	(robo AND advi* OR robo-advi*)
customers	AND ("user*" OR "customer*" OR "consumer*")	
financial advisory service	AND ("financial service" OR "financial services marketing" OR "private banking" OR "financial advice" OR "financial planning" OR "wealth management" OR "asset management" OR "investment" OR "portfolio management")	

3.3. Inclusion and exclusion criteria

We then established a set of inclusion and exclusion criteria (Fig. 2). Firstly, given that robo-advisor services were originally introduced to retail investors around 2010 (Fisch et al., 2019; Snihovyi et al., 2019), we confined the publication period of articles to span from 2010 to 2023. Secondly, considering the relatively nascent nature of the field, we decided to include all peer-reviewed journal articles and IEEE and ACM conference proceedings. This decision is rooted in the fact that these conference proceedings are double-blind peer-reviewed, holding central significance in robo-advisor research. Thirdly, we only included articles in the English language. Fourthly, we read the titles and abstracts of the articles, and when necessary, we also read the full articles. We excluded articles that do not concern implementation of robo-advisory services.

The initial round of reading was done by the first author, who categorized the articles according to the predetermined inclusion and exclusion criteria. Articles considered as borderline cases were subsequently reviewed by the second author, after which the first and second author jointly decided on the inclusion or exclusion.

We then read the remaining 95 articles in full and categorized them according to a predetermined coding scheme (Table 3) by November 2022. Additionally, by the end of August 2023, 37 newly published articles have been added to the corpus, adhering to the same inclusion and exclusion criteria and phases of analysis. Therefore, the final sample is 132 articles (Appendix I).

3.4. Coding and thematic analysis

We initially categorized the 132 articles into ten categories: (1) research questions/aims, (2) theories, (3) methods, (4) findings, (5) robot design, (6) customer features, (7) service encounter, (8) interrelations between robot design, customer features, and service encounter, (9) other themes, and (10) basic assumptions (Table 3). The primary objective of this first coding round was to sort the literature for the second coding round. The categories of robot design, customer features, and service encounter characteristics align with the framework by Belanche et al. (2020). The other categories are either common categories in literature reviews or supplementary categories to those presented by Belanche et al. (2020). The coding of research questions, methods, findings, and basic assumptions in research is important for understanding a body of literature, and enables critical literature analysis (Cecez-Kecmanovic, 2005).

Next, we conducted a second round of coding using a qualitative analysis software NVivo. We further analyzed the literature and identified sub-themes (codes) central to the categories mentioned above (Appendix II). This inductive analysis involved developing codes based on our reading of the literature. Some of the codes were already present in Belanche et al. (2020), serving as foundational elements, but we also found several new themes.

Thus, the contribution of this inductive analysis is that it helped us to confirm and refine existing themes in Belanche et al.'s framework, as well as to uncover new themes. For example, we identified "explainable AI" as a new and essential sub-theme in literature and added it to our codebook and extended framework. In contrast, within "service encounter characteristics" category, we adopted Belanche et al's sub-theme of "involvement level" as a code as such, as our sample confirmed the relevance of this theme.

Finally, we synthesized all categories and sub-themes which are overarching elements under the main themes into an integrative framework. This framework includes the dominant factors that contribute to robo-advisor implementation in frontline services.

Furthermore, this analysis facilitates the creation of a research agenda that critically reflects ongoing debates within the robo-advisor research domain. These debates often stem from divergent research perspectives. For example, one prevalent debate revolves around whether robo-advisors function as substitutes for human financial advisors (Brenner & Meyll, 2020) or merely serve as supplementary entities within financial advisory services (Bhatia et al., 2021). This debate is thoroughly discussed within the research agenda. Understanding and analyzing such attitudes towards robo-advisors can help service providers make informed decisions when implementing business strategies.

4. Findings

Fig. 3 presents the extended framework for the implementation of robo-advisory services. Its constituent parts are robo-advisor design, customer features, service encounter characteristics, and the encompassing ethical, regulatory and legal frameworks that provide the institutional context for robo-advisor services. Service implementation, as depicted in the circle in the middle, necessitates a certain degree of alignment among these constituent elements. The findings section presents each element in comparison to the original framework by Belanche et al. (2020).

4.1. Robot design

Robot design refers to the incorporation of design features within robo-advisor systems or interfaces, aiming to enhance customers' interaction and engagement with robo-advisor systems or applications. The overarching themes in robot design literature are anthropomorphism, explainable AI, level of customer autonomy, and formulation of design principles tailored to achieving specific goals related to robo-advisors and service performance (e.g., adoption-directed design, goal-directed design) (Fig. 4). In robo-advisors, these design features are closely related to different aspects of customer service.

Our analysis shows several differences when compared with the initial framework proposed by Belanche et al. Firstly, anthropomorphism emerges as a central theme in both frameworks as it closely relates to customers' intention to use and adopt the service. However, the discussion in our corpus is more limited in details. For example, the conceptualization of robo-advisors remains primarily confined to the realm of interfaces. These advisors are not physically embodied as robots but often manifest as chatbots, for instance. Consequently, discussions regarding aspects such as gender, voice, and ethnicity have yet to emerge in the context of robo-advisors in financial services. Nonetheless, anthropomorphic factors are indeed embedded in robo-advisory designs, as evidenced by earlier literature. Furthermore, distinct levels of social presence have been explored within robo-advisory literature related to financial services, thereby potentially advancing robot designs within other service sectors.

Secondly, explainable AI is another central and overarching theme within finance related robo-advisory literature. However, it remains unexplored within Belanche et al.'s framework. Notably, the concept of explainable AI has proven to be useful in explaining adoption rates and risk preferences in relation to different customer attributes.

Thirdly, the themes of user control and customer autonomy are

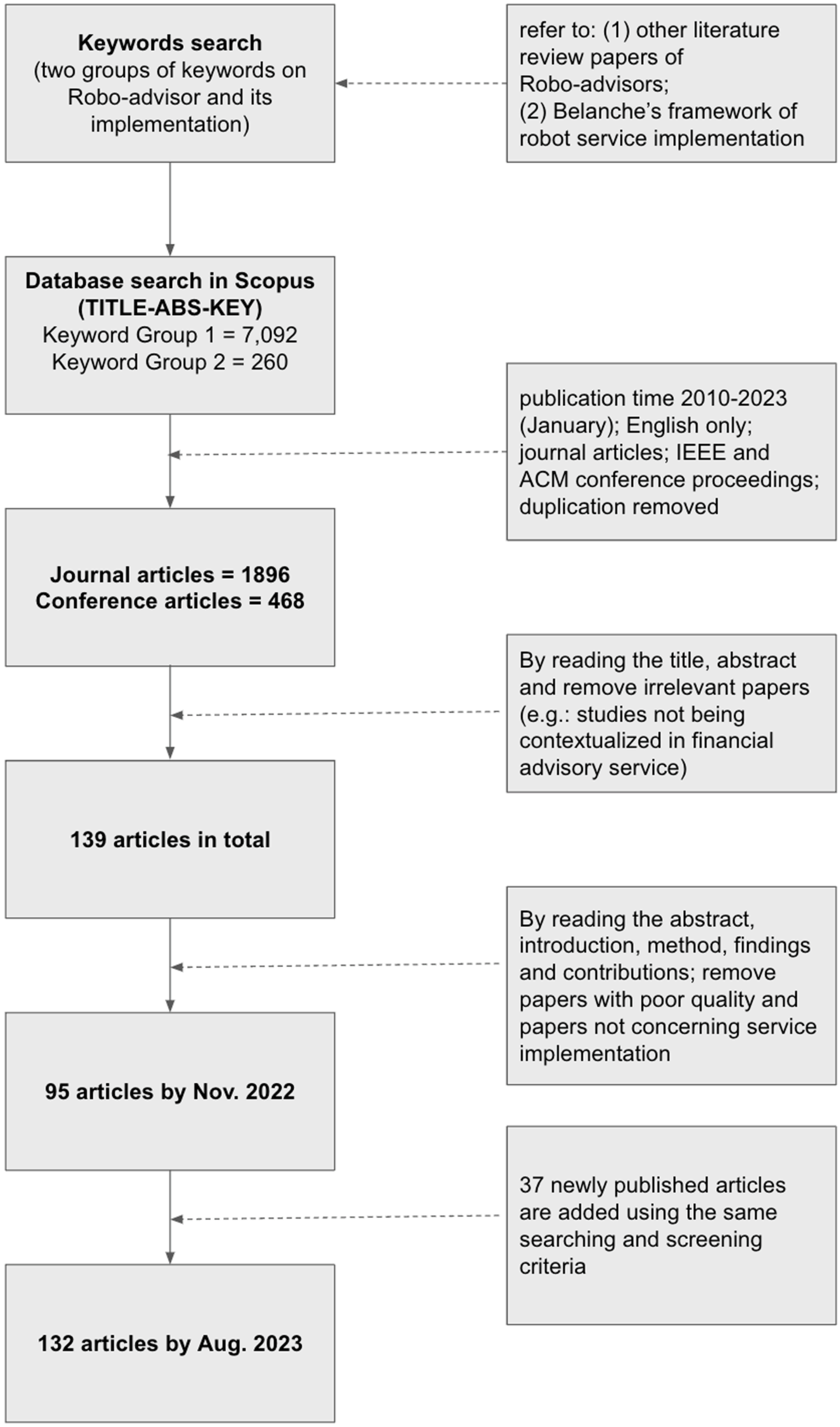

Fig. 2. Article search and selection.

present in both frameworks, yet they manifest with distinct contents within each. In financial services literature, the extent of user control in robo-advisors remains limited due to the lack of physical appearance of or physical interaction with robo-advisors. However, user control is articulated as the customer's level of autonomy concerning the recommended financial portfolio in certain literature. In contrast, when considering the control aspects of robot design within different service sectors, implementation can become notably more complicated. For instance, this may encompass elements such as physical control and direct interaction with the robot. Finally, financial sector literature shows design features aimed at solving financial sector-specific design goals, which do not appear in the literature outside this context.

The themes of anthropomorphism, explainable AI, customer autonomy, and specific design principles in finance literature are presented in

Table 3
Coding and thematic analysis.

Categories	Description
Research questions/ aims	Research objectives, aims and questions
Theories	Theories or theoretical frameworks used in research
Methods	Qualitative or quantitative; how and what data were collected
Findings	Key findings; empirical and theoretical evidence related to service implementation
Robot design	Design features of robo-advisors and how they influence human perceptions and attitudes toward robo-advisors
Customer features	Characteristics and differences of customer groups
Service encounter	How robo-advisors are used in service frontline
Interrelations	Overlaps and intersections between robot design, customer features and service encounter
Other themes	Other relevant themes related to robo-advisor service implementation
Basic assumptions and attitudes	Researchers' beliefs and attitudes about the nature of robo-advisors and the relationship among stakeholders, e.g., service providers, technology, and customers; aims for constructing a critical agenda

more detail below.

4.1.1. Anthropomorphism

Anthropomorphic design attributes are human-like attributes in machines, aiming to improve perceived social presence during interactions with robo-advisors. Social presence indicates the extent to which users perceive human likeness (Adam et al., 2020). Compared to physically interactive service robots applied in other fields, anthropomorphic design in robo-advisors in financial advisory services is still in the early stages, and design features are implemented in user interfaces, such as conversational chatbots (Hildebrand & Bergner, 2021).

The existing body of robo-advisor research revolving around anthropomorphism has predominantly focused on two topics: adoption and risk preference. One prevalent question is whether the inclusion of anthropomorphized design elements within interfaces can affect the adoption of robo-advisors. For example, Kwon et al. (2022) found that social presence significantly impacts customers' intention to use robo-advisors by enhancing perceived usefulness. Similarly, Hodge et al. (2021) found that investors are more likely to rely on a named robo-advisor when the task is perceived as simple. However, in instances where tasks are perceived as complex, investors rely more on an unnamed robo-advisor. Additionally, Ganbold et al. (2021) examined how the avatar design of robo-advisors can increase adoption by reducing customers' algorithm aversion.

The second category of studies delves into the potential impact of anthropomorphizing AI on customers' risk preferences, thus affecting their investment decisions. Empirical evidence from Cui (2022) demonstrates that anthropomorphizing robo-advisor chatbots can lead to risk aversion in investment decision-making. This principle can be utilized for various purposes. For instance, if the service provider aims to promote risk-seeking behavior among customers, objectifying the robo-advisor can lead to customers becoming less sensitive to risk.

Hyun Baek & Kim (2023) conducted a three-experiment study to investigate the relationship between anthropomorphism and investment behaviors of customers in robo-advisors. The results show that customers with a risk prevention-focused mindset are more likely to adhere to regulatory safeguards and have higher investment motivation when presented with a robo-advisor designed with humanlike attributes. Interestingly, this effect does not show for promotion-focused customers. This finding indicates that anthropomorphizing robo-advisors can mitigate uncertainty for risk prevention-focused customers.

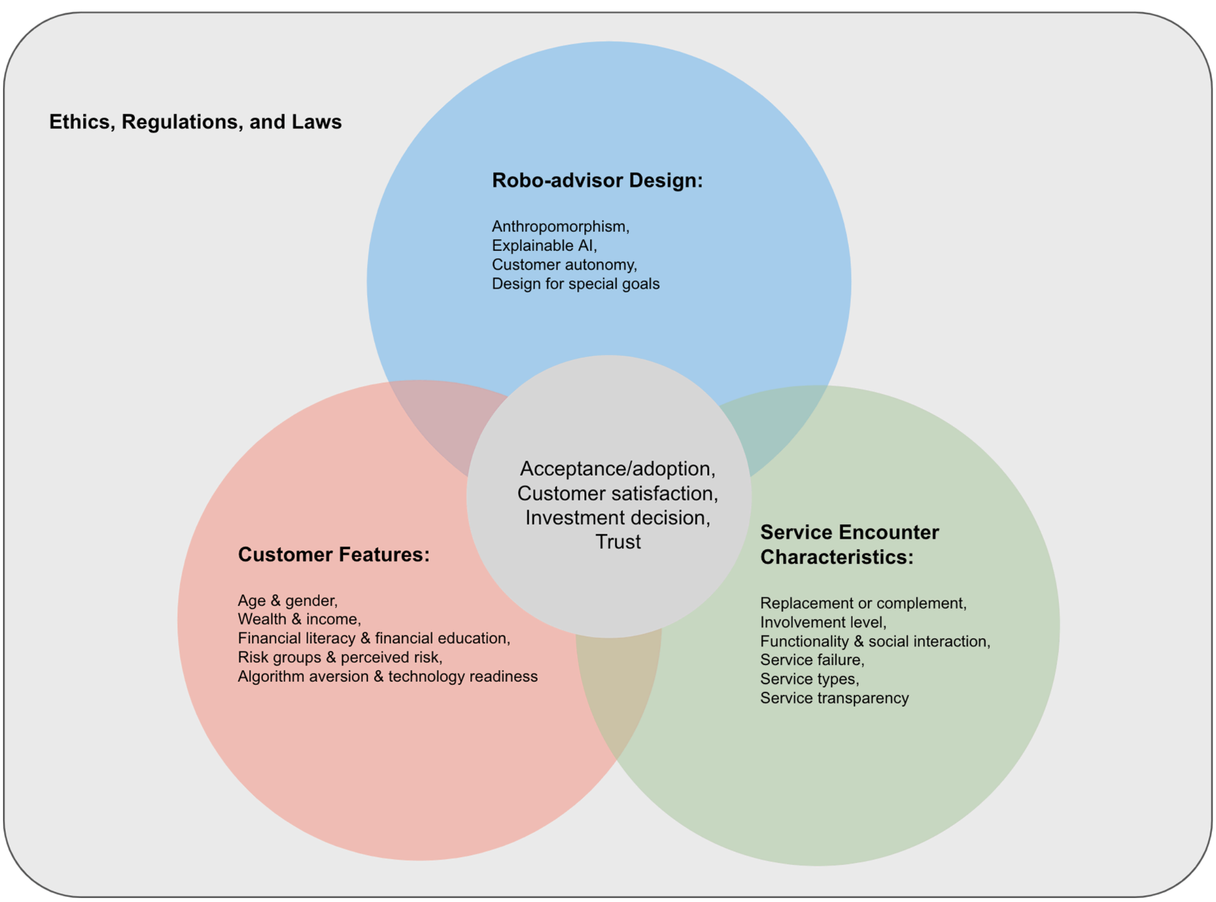

Fig. 3. The extended framework of robo-advisory service implementation.

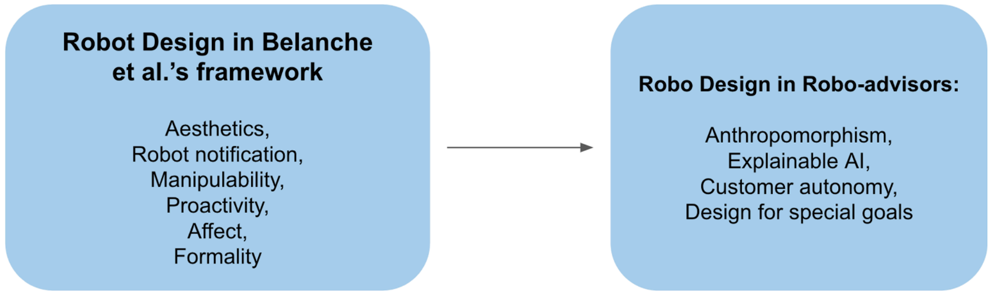

Fig. 4. Elements of Robot Design in robo-advisors and Belanche et al.'s framework.

4.1.2. Explainable AI

Explainable AI can be defined as the ability to explain the mechanisms of an algorithm and discern the rationale behind particular outcomes (Barredo Arrieta et al., 2020), and it highly related to people's decision in using AI (Sakai & Nagai, 2022). In the context of robo-advisors, explainable AI is essential for addressing customers' comprehension of how the robo-advisor works and the reasoning behind its recommendations in financial investment.

According to our analysis, there is a consensus that explainable AI is necessary for robo-advisors for two reasons. Firstly, existing robo-advisors have been found to have insufficient and poor information disclosure in the interface and website (Di, 2022; Mezzanotte, 2020; Xia et al., 2022). Secondly, explainability that increase customers' understanding of the working principles of algorithms can positively affect their trust and reliance on robo-advisors, which can lead to their consequent usage of it (Deo & Sontakke, 2021; Dikmen & Burns, 2022). The second point also highlights that only when the information disclosure is understandable to customers can the benefits of explainable AI be achieved in robo-advisor services. Without human experts' assistance, customers are highly independent in their judgment and understanding when interacting with robo-advisor systems (Salo & Haapio, 2017). Thus, a well-designed interface that incorporates understandable disclosure can benefit service providers. According to Hong et al. (2023), algorithmic interpretability, the ability of a robo-advisor system to provide understandable explanations, can positively affect perceived financial benefits to customers.

Deo & Sontakke (2021b) designed different explanation strategies for complex algorithms used by robo-advisor customers. The result shows that a substantial portion of customers can correctly interpret the explanations of these complex algorithms. By conducting user-centric empirical studies, Naveed et al. (2013) identified three categories of explanations needed by customers: (1) recommendation explanation related to the investment advice provided by robo-advisors, (2) domain-specific information indicating unfamiliar concepts and knowledge, and (3) shared understanding regarding how the system can comprehend the customer's goals.

Additionally, domain knowledge, such as financial literacy, has been demonstrated to be deliverable through explainable AI implemented in robo-advisor interface, as shown by Bertrand et al. (2023). Deo and Sontakke (2021), in their study testing various explanation models, found that feature-based explanations in robo-advisors can enhance customer comprehension and efficiency. In their research, "feature-based" data visualizations in robo-advisors aim to address questions such as "what were the different features influencing robo-advisors' decision or prediction?" However, Bertrand et al. (2023) found that feature-based explanations do not improve the understanding of robo-advisory customers who are non-experts, but dialogic explanations can increase customer trust in the recommendations. Furthermore, explainable AI is expected to make risk-related information easier for customers to comprehend (Mezzanotte, 2020).

4.1.3. Customer Autonomy

Autonomy indicates the level of user control in automated systems. In the context of robo-advisors, they are designed to offer varying levels of customization, allowing customers to adjust the final investment plan according to their personal preferences. An empirical study has reported that user control can have a positive impact on perceived complexity and safety, leading to higher robo-advisor adoption rates (Kwon et al., 2022). Despite the proven competence of robo-advisors in providing financial advice, customers often expect autonomy to make adjustments to the recommended plan generated by robo-advisors or seek confirmation from a human expert (Jung, Dorner, Weinhardt, et al., 2018). However, it's worth noting that interventions involving human experts have shown inferior investment performance when compared to the work of robo-advisors (Ge et al., 2021).

4.1.4. Other design principles to achieve special goals

In addition to the themes mentioned regarding robo-advisor design, other studies have also addressed design solutions and principles to achieve special goals in financial advisory services. For instance, Jung et al. (2018) conducted an exploratory study focusing on robo-advisor design and proposed four design principles: ease of interaction, work efficiency, assisting users in information processing and cognitive load, and advisory transparency. These principles have a significant impact on robo-advisor design, even though the study participants were risk-averse and low-budget customers. Moreover, some design practices involve navigating conflicts between goal-directed design (i.e., design for better financial performance) and adoption-directed design (i.e., design for customers' easy adoption) (Dove et al., 2020). These complexities prompt service providers to define their target customer segments in marketing.

Finally, robo-advisory literature contributes to the broader financial services literature by expanding knowledge of the role of technology in customer interfaces. In contrast to web-based financial services such as internet banking, automated financial services are characterized by their dual role. On one hand, robo-advisors are expected to provide functional assistance to customers, aiding them in the successful completion of tasks. On the other hand, it is also expected to extend social and psychological support to customers, acknowledging the nuanced complexities of their needs and expectations.

4.2. Customer features

Research on customer features mainly discusses the characteristics of customers using robo-advisors (Baulkaran & Jain, 2023; Fulk et al., 2018) or focuses on specific customer groups, such as young retail investors, to understand the factors that can affect their intention to use and their willingness to take advice from robo-advisors (e.g.: Nourallah, 2023; Nourallah et al., 2023). Understanding the features that influence customers' attitudes and behaviors towards robo-advisors can help service providers to define precise customer segments and to tailor product designs and marketing strategies accordingly. In addition to demographics, factors related to robo-advisor customers' financial profiles (e.g., risk aversion) and technology-related factors (e.g., algorithm aversion) can also affect their financial decision-making behaviors (Al-Gasawneh et al., 2022; Belanche et al., 2023; Chang & Wang, 2023).

When we compare the literature on financial advisory services to both robo-advisors and Belanche et al.'s framework (Fig. 5), we observe several differences in customer features. For example, customers with different ages, gender, and levels of technology readiness may exhibit different attitudes towards service robots in financial advisory and in other service sectors. Particularly, customers' behaviors in financial advisory services are complex and their use of robo-advisors can be considered a form of investment decision-making or financial advice-seeking (Adam et al., 2020; Deng & Chau, 2021; Ganbold et al., 2021), which is inherently complex by nature. Consequently, certain customer-specific features may moderate their adoption and use of robo-advisors. For example, customers can be influenced by risk-related factors (i.e.: financial risk and perceived risk) as well as financial-related factors (i.e.: wealth, income, financial literacy, and education). Additionally, customers' attitudes towards algorithms can affect their use of robo-advisor services, a factor not discussed in Belanche et al.'s framework.

Overall, customers in robo-advisory services appear to be more sensitive to and influenced by individual-level risks and concerns in the individual level, because using robo-advisors can be viewed as a form of financial investment. Consequently, factors such as wealth and income play important roles in investment behaviors. However, social and cultural features, which are deemed significant in Belanche et al's framework, have not been extensively studied in the context of robo-advisory services.

4.2.1. Age and gender

The demographics of robo-advisor customers have been extensively discussed in existing literature, covering various topics such as robo-advisor awareness, adoption, satisfaction, and sustainable investment preferences. Age is a primary focus, as robo-advisors are designed for customers who prefer technology over human advisors. Consequently, millennials and generation Z (those born from the mid-1990 s to the early 2000 s) are the target groups for robo-advisory service (Figà-Talamanca et al., 2022; Jung et al., 2019). Older users, in general, report lower satisfaction when using automated tools like robo-advisors, as age negatively affects customer satisfaction (Lourenço et al., 2020). This is consistent with evidence that younger people exhibit a higher intention to use robo-advisors if certain conditions can be met because they are more open with digitalized and AI-based service (Isaia & Oggero, 2022). Moreover, the interrelation between age and intention to use robo-advisors is argued to be driven by customers' relatively higher concerns about retirement (Chhatwani, 2022). For younger generations, the perceived usefulness of robo-advisors is the primary factor driving their adoption (Figà-Talamanca et al., 2022). Studies focusing on customers' initial trust in robo-advisors show that young retail investors (18–29 years old) can be influenced by social media information-seeking, and the ability of robo-advisors to perform expected tasks can address initial trust concerns (Nourallah, 2023; Nourallah et al., 2023).

Gender is also a significant factor that can influence the customers' level of awareness and perceptions about robo-advisors. Women generally show a lower intention to use robo-advisors compared to men (Seiler & Fanenbruck, 2021). When it comes to selecting AI-based financial services, women often exhibit greater moral sensitivity and maintain more critical attitudes towards potential unethical behavior (Piotrowski, 2022). However, there are divergent conclusions regarding gender and sustainable investment. An empirical study conducted among robo-advisor users in Nordic countries showed that female customers tend to prefer sustainable investment choices (Faradynawati & Söderberg, 2022). On the other hand, Au et al. (2021) found, based on a survey of German university students, that being male is positively associated with the use of sustainable robo-advisors.

4.2.2. Wealth and income

Customers' income and wealth are significant factors in financial decision-making. Wealth, including income and net wealth available for investment, is considered a part of customers' socio-demographic characteristics. It has been discussed alongside age, gender, and education as these interrelated features can affect individuals' use of robo-advisors (D'Hondt et al., 2020; Waliszewski & Warchlewska, 2020).

The average monthly income of customers can affect their acceptance of robo-advisors (Kraiwanit et al., 2022). Results from a between-subject experiment have indicated that customers with high net worth are less likely to use robo-advisors when both conventional human services and robo-advisors are provided (Northey et al., 2022). In line with this, medium-income households are considered the target group of robo-advisors (Tiberius et al., 2022). A dataset covering 22,972 investors shows that customers with lower incomes benefit more from using robo-advisors because algorithms perform better even during crises (D'Hondt et al., 2020). Household income is also a factor impacting on customers' satisfaction with robo-advisors (Waliszewski & Warchlewska, 2020). Research has also shown that mid- to low-income customers need support from robo-advisors because they have limited financial assistance resources (Fan & Chatterjee, 2020; Jung, Dorner, Weinhardt, et al., 2018).

4.2.3. Financial literacy and financial education

Financial literacy, an individual's capacity to understand concepts and use skills related to financial management, has been discussed in two aspects in robo-advisor studies: objective knowledge measured by expertise (i.e., standardized measurement test) and subjective knowledge (i.e., self-assessment) reported by customers themselves (Lewis, 2018). An empirical experiment conducted in Germany shows that users of robo-advisors tend to have lower levels of financial literacy (Seiler & Fanenbruck, 2021), and subjective financial knowledge is correlated with customers' intention to use robo-advisors (Kraiwanit et al., 2022). Among US customers, subjective financial knowledge is positively associated with robo-advisor use intention and adoption (Fan & Chatterjee, 2020).

Moreover, financial literacy influences customers' adoption of robo-advisors by mediating "overconfidence", which indicates the discrepancy between subjective and objective financial knowledge. Robo-advisors appear more attractive to overconfident investors. For

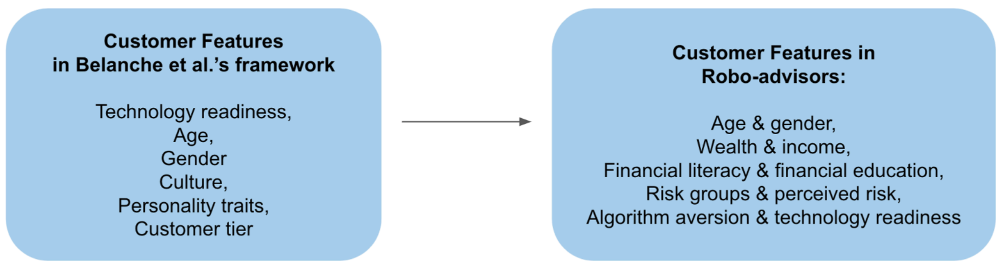

Fig. 5. Elements of Customer Features in robo-advisors and Belanche et al.'s framework.

example, Piehlmaier (2022) found that adopters of robo-advisors tend to be overconfident customers who believe their obtained information is more precise than it actually is. In line with this finding, Lewis (2018) suggested that robo-advisors should target customers with overconfidence because human-AI interaction can provide them with a comfortable environment to assess their actual financial literacy without the potential embarrassment of communicating with a human advisor.

At the same time, financial education aiming to improve customers' financial literacy increases the investors' willingness to delegate their financial decision to robo-advisors. Specifically, financial education can deliver detailed information regarding the underlying algorithms applied in robo-advisors, encouraging customers to use robo-advisors (Litterscheidt & Streich, 2020). According to an in-depth analysis of customers who already use robo-advisor, those who invest in high-risk assets tend to have better financial knowledge and experience (Oehler et al., 2022). Moreover, robo-advisors should provide financial knowledge because customers were found to lack understanding of financial terms when interacting with robo-advisors (Salo & Haapio, 2017). Also, for regions with low financial literacy, e.g., Latin America (Méndez Prado et al., 2022), a lack of financial education presents the main hurdle for customers to adopt robo-advisors. Summarizing these findings can be challenging as the field relating financial literacy to robo-advisors is relatively new, and more empirical studies and *meta*-analyses are likely needed. Nonetheless, the current findings indicate the importance of finding solutions to provide financial education to customers through robo-advisors. This is because robo-advisor services can lower the entry bar for customers in financial investment.

4.2.4. Risk groups and perceived risk

Risk plays a significant role in customers' decision-making, especially in financial investments involving high stakes, such as the cost of time and money for customers. In our context, a customers' risk group is related to individuals' investment behaviors, which can be assessed through a standardized survey at the beginning of the financial advisory service. This process helps categorize customers into risk groups to provide them with corresponding financial products. Perceived risk is associated with customers' subjective evaluation of risk, which can be activated during their interaction with the robo-advisor service. For example, it may involve concerns about data security and the possibility of losing money.

In general, robo-advisors are designed to cater to risk-averse consumers and address the market inefficiencies of traditional human advisory services (Jung, Dorner, Weinhardt, et al., 2018). Customers with higher risk tolerance are more likely to embrace robo-advisors (Oehler et al., 2022). However, robo-advisors do not demonstrate superior risk assessment abilities compared to conventional services because they utilize the same approach as their human counterpart (Tertilt & Scholz, 2018). According to Tertilt and Scholz, the risk-profiling process adopted by robo-advisors appears conservative and has not been extensively discussed in current literature.

The perceived risk negatively impacts customers' intention to use robo-advisors (Al-Gasawneh et al., 2022; Gerlach & Lutz, 2021). This may be due to customers' reluctance to face potential losses caused by their incompetence in using this technology (Al-Gasawneh et al., 2022). Interestingly, the willingness to take financial risk does not improve robo-advisor adoption, even among overconfident customers (Piehlmaier, 2022). In some cases, customers' risk aversion can increase when they perceive that anthropomorphized AI is making decisions (Cui, 2022).

Moreover, it's important to note that the perceived risk is not fixed; it can be moderated by factors such as increased endorsement and improved perceived security (Al-Gasawneh et al., 2022; Gerlach & Lutz, 2021). Belanche et al. (2023) conducted a study exploring four types of perceived risk in robo-advisory services: performance risk related to system issues or incorrect advice, financial risk referring to potential monetary losses, social risk associated with opinions from peers, and time risk, which relates to the time investment required to learn and use robo-advisory services. Their results indicate that financial risk and time risk shape customers' overall risk perception, consequently impacting customers' loyalty.

4.2.5. Algorithm aversion and technology readiness

A robo-advisor is essentially a type of AI-empowered technology, and as such, customers' features related to technology and algorithms play an important role in robo-advisor studies. Algorithm aversion has been identified as a factor leading to reduced adoption of robo-advisory services, despite that robo-advisors have demonstrated superior performance compared to human experts. Overcoming algorithm aversion represents a substantial challenge for robo-advisors' development (Filiz et al., 2022).

However, Ganbold et al. (2021) found that the barrier of algorithm aversion can be mitigated through the design and implementation of avatars in the robo-advisory service. Avatars enhance the perception of robo-advisor competence, thereby increasing customers' trust and reliance on these systems. Additionally, Chang & Wang (2023) discovered that algorithm aversion effects exist in automated wealth management services, and it tends to be weaker among prevention-focused customers compared to promotion-focused customers.

Technology readiness has been studied in other AI-empowered customer services but few findings in the robo-advisor context. Technology readiness determines customers'propensity to rely on AI-empowered technology, and they choose not to use it because they are not ready (Belanche et al., 2020; Blut & Wang, 2020). Flavián et al. (2022) tried to decompose technology readiness into different aspects to explain customers' intention to use robo-advisors. According to this research, technological optimism increases and insecurity decreases customers' intention to use robo-advisors. Surprisingly, technological discomfort has a positive influence on robo-advisor adoption, likely due to AI's ability to assist those with lower technological skills.

4.3. Service encounter characteristics

Belanche et al. (2020) suggest that service encounter characteristics contextualize robots in service contexts. In the case of AI-empowered financial advisory services, unique features have emerged in its service encounter, when compared to the original framework (Fig. 6). On the other hand, several themes are the same as in the framework by Belanche et al, such as the level of involvement in robo-advisor-customer interaction, service failure and customer complaints, service stages, and robo-advisor's relationship with human employees.

In terms of service encounter, the interaction between customers and robo-advisors is more complicated because financial investment is not a short-term behavior, and customers have the risk to lose their money by using this service. At the same time, financial markets and services are difficult for customers with little financial knowledge to understand (Hilgert et al., 2003; Moore, 2003). Thus, in comparison with frontline employees in other service sectors, human financial advisors play more important roles in frontline service to reduce the uncertainty of customers and elicit their purchase (Haslem, 2010; Morduch & Schneider, 2017). Therefore, many studies debate whether AI can replace the role of human advisors. Besides, the involvement level in robo-advisory literature solely indicates the investment amount, and other forms such as interaction time and effort, and as mentioned by Belanche et al', other forms of involvement have not been explored in robo-advisory service yet.

Like other service robots, robo-advisors can fulfill customers' functional requirements (e.g.: transaction, financial investment, etc..) as well as provide social support. Regarding after-adoption service encounters, robo-advisory literature shows insufficient findings compared with other robot services. Overall, the transparency issues existing in robo-advisory operations are also discovered as obstacles for customers' trust and adoption of recommendations.

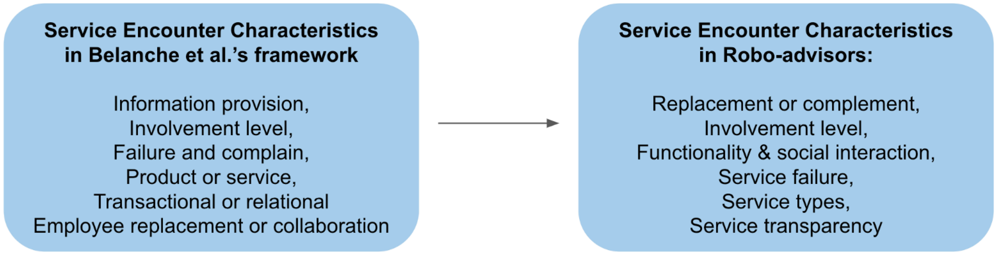

Fig. 6. Elements of Service Encounter Characteristics in robo-advisors and Belanche et al.'s framework.

4.3.1. *Replacement or complement*

As robo-advisors gain more customers in the financial service market, the market share of traditional advisory services is expected to decline (Tiberius et al., 2022). This trend may impact the employment of human advisors in traditional retail banking, as robo-advisors become competitors to these employees (Gomber et al., 2018). The question arises: can robo-advisors replace human advisors? Empirical evidence suggests that robo-advisors perform better in asset management, even during financial crises (D'Hondt et al., 2020; Lightbourne, 2017). Similarly, Liu et al. (2023) compared portfolio returns between robo-advisor customers and those who did not use robo-advisors. In terms of similar investor and portfolio characteristics, robo-advisory users had fewer losses during the pandemic crisis; however, the portfolio returns were similar in a normal market.

However, most studies indicate that robo-advisor services cannot replace all advisory services and are instead supplementary to financial advisors (Bhatia et al., 2021; Chhatwani, 2022; Filiz et al., 2022). In addition to functionality, customers require emotional connections that robo-advisors are not yet able to provide, as they lack empathy and the ability to maintain client relationships during the service encounter (Bhatia et al., 2021; Boustani, 2022). Researchers have concluded that human intervention is necessary because a fully automated process may lead to negative emotions, such as retirement worries among investors (Chhatwani, 2022). Furthermore, while robo-advisors can provide generic advice, they may struggle to address specific investment queries. An experiment has also demonstrated that customers prefer human experts to confirm the results generated by robo-advisors (Jung, Dorner, Weinhardt, et al., 2018).

4.3.2. *Involvement level*

Customer involvement level typically indicates an individual's interest in buying and consuming a product. Low-level involvement products are usually inexpensive and low-risk. According to Belanche et al. (2020), involvement level significantly influences the acceptance of service robots. Customers make final decisions based on their involvement, evaluating how complex and relevant the service is to them. The level of customer involvement also determines the amount of investment in robo-advisors. In financial investment, reducing the involvement level by encouraging customers to start with a small amount of money can increase their willingness to use robo-advisors (Belanche et al., 2019). Studies have also shown methods to increase involvement levels. First, providing customers with more options for selecting financial products can increase their investment in robo-advisors (Riitsalu & Uusberg, 2021). Additionally, implementing a conversational chatbot can increase the assets allocated in the portfolio recommended by robo-advisors because chatbots can enhance customers' affective trust more than non-conversational robo-advisors (Hildebrand & Bergner, 2021).

4.3.3. *Functionality and social interaction*

From the customer's perspective, robo-advisors are responsible not only for completing various tasks (e.g., transactions, calculations, and predictions) but also for effective interactions and maintaining social relationships (Cheng et al., 2019; Hildebrand & Bergner, 2021; Lourenço et al., 2020; Northey et al., 2022). In terms of functionality, robo-advisors promise customized financial investment portfolios and tailor financial advice according to individual preferences, risk groups, wealth, and more (Jung, Dorner, Glaser, et al., 2018). However, robo-advisors are criticized for their limited individualization when it comes to recommending portfolios because they often ignore significant variables during the portfolio generation process (Faloon & Scherer, 2017; Scherer & Lehner, 2023). This lack of individuality results in generic advice given to different customers and limits the economic benefits of robo-advisors (Scherer & Lehner, 2023).

As investment can be a long-term service rather than a one-off transaction, customers have strong social and emotional requirements in financial service encounters (Beltramini, 2018; Mogaji et al., 2021). These non-functional aspects collectively affect customers' perceptions, user experiences, satisfaction, trust, adoption, and their subsequent intention to use robo-advisor. Previous studies have discussed these features in relation to the design and the psychological mechanisms underlying customers' interactions with robo-advisors. These studies have demonstrated that the complexity and intelligence of robo-advisors are more advanced than those of service robots used in other domains. However, the ability to fulfill functional tasks or superior performance compared to human advisors does not necessarily translate into customer adoption.

4.3.4. *Service failure*

Current research on robo-advisor service failures primarily centers on issues of responsibility: which party should be held accountable for robo-advisor's mistakes? Studies in law suggest that the firm offering the service should assume responsibility for algorithmic failures because the fiduciary standard "provides an adequate liability scheme for current robo-advisors" (Lightbourne, 2017). At the same time, providing customers with financial knowledge can help them identify and avoid possible mistakes made by the algorithm (Dikmen & Burns, 2022). Nevertheless, research on service failures and unintended consequences remains still in its infancy.

4.3.5. *Service types*

Most robo-advisor services offer generic advisory services, such as financial asset planning, management, and maintenance. Other types of robo-advisors have also emerged, including peer-to-peer lending (P2P) and robo-advisors specifically designed for pension and retirement planning (Lee, 2020; Lourenço et al., 2020; Turner & Klein, 2021). Recently, some studies have focused on a new type of robo-advisor that provides ESG (environmental, social and governance) investment portfolios (Au et al., 2021; Brunen & Laubach, 2022; Faradynawati & Söderberg, 2022) or low-carbon funds (Shan et al., 2022) as investment preferences for customers. Shan et al. (2022) found that automated funds investing in low-carbon funds tend to outperform their competitors. As a selling point for robo-advisors, providing sustainable investment choices can evoke the interests of customers in conventional robo-advisors, but there are still gaps between general interest and real action (Brunen & Laubach, 2021).

4.3.6. Service transparency

Service transparency in advisory operation helps enhance customer confidence, assuring them of service quality and the consistency of provided advice (Nain & Rajan, 2023, 2023). Zhu et al. (2023) find transparency issues existing in two processes of robo-advisory service encounters: when customers answer configuration questions and when they read the recommended portfolio. These issues represent the main hurdles for customers' investment decision-making.

4.4. Ethics, regulations and laws

The literature on financial advisory services underscores the significance of the institutional context in the implementation of robo-advisory services. Ethics, regulations, and laws play a pivotal role in defining both the feasible and desirable aspects of services within an institutional context. This perspective is notably absent in Belanche et al.'s original framework. Nevertheless, these fundamental elements are crucial in establishing a robust, equitable, and transparent financial market, as well as ensuring adequate protection for customers when engaging in financial activities. Existing literature has mostly focused on the impact of ethics and regulations on customer features and robot design, leaving multiple gaps for further research.

Compared to traditional advisory services, robo-advisor customers have expressed fewer ethical concerns because algorithms are believed to be reliable, and their outcomes are difficult to manipulate by humans (Piotrowski, 2022). However, as robo-advisors continue to rapidly evolve, customers are likely to raise more ethical concerns. Ethical considerations are crucial in building a trustworthy relationship with customers, which can contribute to the overall financial well-being of customers (Aw et al., 2023). For instance, the perceived integrity of robo-advisors can have a positive impact on customers' perception of service providers as ethical institutions (Piotrowski, 2022). Mogaji et al. (2021) emphasized that robo-advisor's ethicality is particularly crucial for vulnerable customers who are susceptible to financial harm. Furthermore, conveying ethical standards during data collection and AI processing can reduce customers' vulnerability and improve their experience with robo-advisors.

Regulations and laws pertaining to robo-advisors have been examined within the context of various regions and countries. Firstly, some studies have emphasized the role of regulations in information disclosure (Chia, 2019; Di, 2022), which relates to the service designs and the customers' need and ability to absorb information related to financial products. Secondly, researchers point out that service developers and providers have stringent regulatory requirements that they need to comply with, such as those related to data security, customer privacy, and non-discrimination of customers (e.g. Crosman, 2019). Furthermore, in many regulatory contexts, demonstrating the transparency of algorithms is a prerequisite for service implementation, which poses a major challenge for service developers and providers, as many AI tools are not easily explainable (Burrell, 2016; Canhoto, 2021; Paterson, 2021; Steennot, 2022).

However, several authors point out that robo-advisors, along with other AI products in the finance sector more broadly, may contribute to customer protection compared to other service forms if robo-advisory services are not misleading (Steennot, 2022). They may also address cybersecurity challenges in the banking sector (Gopal et al., 2023). Furthermore, some papers have highlighted that robo-avisors may promote financial inclusion in society (Lee, 2020).

To strike a balance between these technological opportunities and challenges, policymakers should be cautious of policies that may hinder technological innovation and flexibility in robo-advisory services (Brummer & Yadav, 2018; Zunzunegui, 2022). However, there is an overall lack of literature that specifically focuses on ethics, regulations, and laws in robo-advisory services within the finance sector, which is surprising due to the highly regulated nature of the financial industry. The development of regulatory frameworks is an important part of implementing service robots in the industry (Di, 2022; Salo-Lahti, 2022), as it can either constrain or enable their implementation. Future research should also consider how to ensure secure banking services for all customer groups and identify the areas within the banking sector's operations where robo-advisors can provide the greatest societal benefits.

5. Discussion

This review underscores that service robots constitute a rapidly developing area of research and practice in finance and other service sectors. The extended framework (Fig. 3) indicates that effective service robot implementation requires a certain degree of alignment among the constituent elements, while also suggesting new avenues for research. In the subsequent sections, we delve into the key debates related to the central themes within the framework, provide managerial implications, and outline a critical research agenda.

5.1. Implications for service implementation

We observe that the interrelations among robot design, customer features, and service encounter characteristics in AI-empowered financial advisory services are complex and have been explored from various theoretical perspectives within existing robo-advisory research. These perspectives encompass key theoretical frameworks, including technology adoption theories (Kwon et al., 2022; Yeh et al., 2023), theories related to financial advice and customer behavior (e.g., Al-Gasawneh et al., 2022; Deng & Chau, 2021), and theories associated with the attributes of artificial intelligence and service design. Moreover, the literature increasingly incorporates theories rooted in institutional contexts. To advance robo-advisor implementation, three central debates are to be addressed.

5.1.1. Enhancing robo-advisor design

The review indicates that the development and implementation of robo-advisors are primarily driven by service providers (Fisch et al., 2019), with little customer involvement in the design process. Furthermore, the main motivations for implementation have been commercial in nature. As a result of this dominant focus, legislative considerations, for example, have lagged behind.

Enhancing robo-advisor design requires a more thorough consideration of customer needs. Specifically, the design features of robo-advisor systems and interfaces have remained largely unchanged due to the limited input from customers. Our analysis indicates that empirical studies on robo-advisors have primarily focused on customer adoption and decision-making as the central objectives of robo-advisor design (Adam et al., 2020; Ben David et al., 2021; Cui, 2022; Hildebrand & Bergner, 2021). The effectiveness of robo-advisory service relies on the robo-advisor system, with the interface serving as the sole means of interaction and communication. While customers may use existing robo-advisor systems due to a lack of alternatives, this does not necessarily imply their satisfaction with them. Often, their genuine needs and concerns remain overlooked and underdeveloped.

Empirical evidence supporting the necessity of anthropopathic design in robo-advisor contexts is absent. Researchers have primarily relied on assumptions and deductions from robot design in other sectors, rather than considering the unique nuances of the financial service context. Some researchers suggest that the incorporation of human-like characteristics may enhance trust (Hildebrand & Bergner, 2021) and improve customers' perceptions of robo-advisory services (Cui, 2022; Ganbold et al., 2021). However, other issues raised in user-centric studies, such as concerns related to information transparency and comprehensiveness (Jung et al., 2018), should also be considered in robot designs.

Addressing these issues could involve various methods, such as employing comprehensible data visualization or utilizing advanced AI technologies like OpenAI's ChatGPT, developed with optimized language models and learning techniques. Nevertheless, these potential solutions lack investigation or practical design implementation. Future research could focus on involving end customers in the design and implementation process to gather empirical evidence and refine these approaches. This suggestion aligns with the human-centered AI approach, which emphasizes that high-level human control, including usability testing, iterative refinement, and evaluation, should hold equal importance to high-level automation in AI-empowered systems (Shneiderman, 2022).

Furthermore, robo-advisor designs must adhere to regulatory requirements, a task that is far from straightforward. One significant challenge stems from the fact that robo-advisor developers often operate within the international software business market, while their implementations tend to be predominantly local. This presents difficulties in crafting algorithms that can be seamlessly adapted to fit within the confines of local legal frameworks. Additional significant challenges associated with regulatory requirements pertain to the transparency and explainability of robo-advisory systems. Both the research on institutions and their relation to robot designs are still in their early stages.

5.1.2. Which users should be prioritized in robo-advisor development?

Predominant research on robo-advisors has primarily focused on early adopters, examining the factors influencing their intention to use and adopt these services, while also developing strategies to attract similar customers. This focus has persisted the variations in influential factors across different regions. However, it is worth noting that early adopters may not represent the customer segment that stands to benefit the most from robo-advisors or those who truly need the support and assistance offered by these services.

In many cases, individuals with lower education levels, limited income, and constrained budgets can reap greater advantages from robo-advisors (D'Hondt et al., 2020; Jung et al., 2018). This demographic is often referred to as "lay customers" or "lay investors" in literature (Hayes, 2021; Tan, 2020; von Walter et al., 2022). It is suggested that to increase awareness and adoption of robo-advisors among lay customers, researchers and service providers should encourage their "first use" of a robo-advisors and emphasize the benefits they can derive from them (Bhatia et al., 2022). Once these customers experience the advantages of robo-advisors, their likelihood of continued usage is likely to increase.

Some tactics to reduce the initial barriers to usage include reducing the required involvement and enhancing understanding of both financial knowledge and AI systems (Northey et al., 2022). This is particularly important because some customers may abandon the service when faced with difficulties in comprehending the investment product prospectuses, which are typically presented in written form within robo-advisors (Salo & Haapio, 2017).

However, it's important to acknowledge that these strategies may not be sufficient to enhance robo-advisor adoption among lay customers. Further research is needed on customers with relatively low incomes, limited budgets, and lower levels of financial literacy.

5.1.3. The need for human intervention in AI-powered services

Instead of debating whether robo-advisors should be seen as replacements or complements to traditional financial advisory services, a more insightful approach is to examine *when* and *why* customers seek the involvement of human experts. This examination can reveal the underlying demands of customers who are interacting directly with robo-advisor services. Approaching the relationship between robo-advisors and human experts with a contrasting mindset may not necessarily stimulate innovation in financial technology or improve the quality of existing robo-advisor services.

It is important to note that robo-advisors serve a broader purpose than being mere distribution channels for retail banks' services. Our analysis suggests that robo-advisory services represent a disruptive innovation in customer service, introducing new paradigms and appealing to a new generation of users characterized by distinct financial behaviors compared to their predecessors.

Existing research indicates that customers may seek human experts to provide additional confirmation for robo-advisors' recommendations (Jung et al., 2018), address individual-specific questions (Chhatwani, 2022), and establish emotional connections, including empathy and reassurance (Chhatwani, 2022; Hildebrand & Bergner, 2021). However, the underlying reasons for these requirements have not been thoroughly investigated. These needs may be intertwined with factors such as the transparency of information within robo-advisor systems, customers' financial literacy, or behavioral biases influenced by social and cultural factors.

Consequently, the involvement of human support in the advisory service, such as through a chat function or customer service, may not fully resolve these issues (Zhu et al., 2023). There is a need for further research from a social-technical perspective to delve into the causality of these challenges, treating robo-advisors as a social-technical phenomenon rather than just a tool. Subsequent targeted actions can then be taken based on these insights. This approach aligns with the suggestion put forth by Hentzen et al. (2022)'s review paper.

User experiments and evaluations can effectively identify problems in existing robo-advisor systems and service implementations to address the aforementioned issues. This proposition emphasizes the importance of a more user-centric design process.

5.2. Unintended consequences of implementing service robots in financial advisory services

The implementation of AI-empowered financial advisory services may bring multiple benefits for service providers and their customers. However, introducing new technologies to the market always involves several unintended consequences, showing the result of current implementation deviating from the initial goals. Our literature analysis indicates that existing research in robo-advisors has touched upon this topic in some aspects, even though with a limited numbers of articles.

The primary unintended consequence is that customers require human experts' intervention to double-confirm the decisions made by AI. This has been discussed in detail under section 5.1.3. Additionally, some articles investigate negative consequences. For example, literature under the sub-theme of "complete or complement" discusses whether human labor can be replaced by robo-advisors and the possible unemployment consequences for human advisors. Articles under "ethics, regulations and laws" and "service failure" focus on the responsibility for algorithmic failures.

A limitation in the literature primarily stems from the fact that existing research has predominantly focused on areas such as early-stage design and asset management, rather than conducting in-depth analyses of how implementation projects progress and the challenges associated with them. Moreover, the lack of long-term empirical studies among customers who already use robo-advisors also contributes to the absence of research detecting unpredicted consequences. This gap represents an important area for future studies.

Based on the integrative framework, we also highlight potential issues regarding isolation and imbalance between the four themes. We emphasize the consequences of neglecting customers' experience in both service design and in information system design.

Firstly, the theoretical framework proposed by Belanche et al. (2020) and our expansion of it (Fig. 3) emphasize important perspectives for understanding unintended consequences and prepare for negative consequences by consideration of ethical issues in each stage of service implementation. According to the framework, the successful implementation depends on considering robo-advisor designs, customer features, service encounter characteristics, and ethics, regulations and laws related to service development and adoption. As a consequence, the absence of consideration for these perspectives may lead to implementation failures or the emergence of unintended consequences.

Secondly, the intertwined interrelations between these themes and sub-themes constitute the complex nature of customers' decision making in financial investment and their adoption of an AI's decision. Different from service robots in other use scenarios, some customers can be sensitive and cautious in making high-stake decisions such as on financial investment. At the same time, some features such as risk-aversion and algorithm-aversion can be evoked in customers' using robo-advisors based on our analysis. Moreover, these factors can have different influences as the situation evolves, for example, under crises such as COVID-19, in different countries and regions, etc. This is because the customer behavior in using robo-advisors is difficult to forecast. To mitigate the negative consequences, situated customer experience should be prioritized and evaluations in different stages of robo-advisory service implementation should be carefully conducted. The practical implications can be seen in Section 5.1.1.

These findings contextualized previous research regarding unintended consequences of service robots in general in financial advisory services (e.g.: Crolic et al., 2022; Pitardi & Marriott, 2021; Ryoo et al., 2024). As an extension, we addressed that the customers' attitude towards service robots can be highly contextual, which limits the design of generalizable robot features or service encounter processes. Aligning with our framework, such customer behaviors in service encounter situations should be considered when planning service processes and designing robots.

Nevertheless, the interaction between customers and AI-empowered financial advisory service remains a gap in the broader literature (Lu et al., 2020; Tsai et al., 2021). For instance, several important research avenues, closely relevant to financial services research, include investigations into fraud and customer misbehavior (Fisk et al., 2010), service experience co-creation (Blut et al., 2020), the autonomy of employees and customers in service encounters (McLeay et al., 2021; Wirtz et al., 2018; Xiao & Kumar, 2021), and various ethical considerations (Lobschat et al., 2021). For example, these ethical considerations encompass consumer concerns regarding AI-related privacy (Pitardi & Marriott, 2021) and Digital Corporate Responsibility (Lobschat et al., 2021; Wirtz et al., 2021), which addresses ethical dilemmas linked to AI technology. Our literature review shows that these topics are still in their nascent stages within financial advisory service research.

5.3. Managerial implications

In section 5.1, we discuss three overarching issues to consider when service providers are making decisions in implementing robo-advisors in customer-facing services. In this section, we introduce managerial implications in broader aspects, as well as elicit managerial takeaways to implementing AI in general financial services.

Firstly, the primary managerial implication of this research lies in recognizing that the implementation of AI-empowered services necessitates a comprehensive consideration of robot design, customer features, service encounter characteristics, as well as ethics, regulations, and laws. As of 2023, various AI-empowered solutions have achieved widespread integration into both business and consumer applications in financial services. However, as is often the case with new technological innovations, there exists a risk that AI strategies may be developed in isolation from the broader core business context. This emphasizes the importance of aligning AI strategies with actual customer needs and overarching business objectives, as well as under an ethical and legal frame. Isolated projects with unbalanced considerations in any aspect of the framework can result in challenges during technology implementations and lead to various unintended consequences. The framework proposed in this research can provide guidance in developing holistic strategies.

Secondly, customer features and customer's individual experiences and perceptions of robo-advisors are rapidly evolving due to the widespread adoption of AI services in everyday life. Even though customers can be sensitive regarding terms of financial investment and the adoption of AI's decisions, there are strategies that can be used in different aspects., These include implementing anthropomorphized design or explainable AI; targeting customers who embrace robo-advisors and show higher use intention; and using strategies to encourage customers to invest small amounts. All the themes and their sub-themes introduced in our framework and their effects on service adoption, acceptance, and customer trust can offer valuable insights for predicting customer behavior and reactions.

Thirdly, launching and implementing AI-empowered services presents an enormous challenge for financial service providers. These services are often developed by various providers outside the industry. Firms themselves often assign responsibilities for AI-empowered service development on their marketing departments, necessitating new skills for these functions. Moreover, given the evolving nature of regulation and ethics, there is a continual need to keep pace and develop capabilities. Additionally, the implementation of these services affects all departments, demanding extensive change management within organizations. Another significant challenge lies in coordinating the division of labor and fostering cooperation between industry companies and their external service providers. An inter-organizational perspective becomes valuable in addressing this aspect.

Finally, companies need to restructure their service processes and customer encounters. This includes considering the new services enabled by AI, along with the collection and management of customer data, and providing training for personnel.

6. A critical agenda for further research in robo-advisors

Our analysis shows several research gaps, as well as themes and questions that have remained under-researched. These are summarized in Table 4.

Robo advisory service providers often confront complex decisions when implementing services, striving to optimize limited resources for an improved customer experience and heightened satisfaction. Moreover, the rapid evolution of AI-empowered technology and unpredictable shifts in customer behavior pose significant challenges for practitioners in making effective managerial decisions. As a result, they require a framework to prioritize certain goals while deferring others.

Robo-advisors have proven their commercial value by reducing labor costs and enhancing service performance. There is also an increasing acknowledgment of their societal value in providing financial planning and management services to individuals in need of expert support. In academia, a state-of-the-art research agenda is necessary. Many research papers have focused on similar research questions, often exploring variables related to customers that impact their perception or adoption of robo-advisors.

Nonetheless, robo-advisors have evolved beyond their initial stages, prompting us to contemplate how the next generation of robo-advisors can be iterated and effectively implemented in the service frontline.

Furthermore, the successful introduction and implementation of robo-advisor necessitates closer collaboration among actors across different service sectors, from robot design to frontline service delivery. It also requires knowledge sharing among scholars from various disciplines, including information systems, service marketing, behavioral finance, and law. Our research identifies an evident gap in cross-sectional and cross-disciplinary studies that integrate robot design, customer features, and frontline service encounters in the context of robo-advisor. Furthermore, empirical studies based on real customer usage are essential to address this gap.

Finally, future research on robo-advisors should shift its focus to exploring the evidence and theories pertaining to the post-adoption phase. Ostrom et al. (2019) have categorized customer acceptance of AI services into three stages: approval, adoption, and usage. However, current research predominantly revolves around the 'approval' and 'adoption' stages, representing relatively early phases of robo-advisor service adoption.

Table 4
Potential questions to be explored in further research in robo-advisors.

Themes	Research topics
Robot Design	(1) Investigating further into explainable AI as an instrument for enhancing transparency, understanding, trust, and financial domain knowledge. (2) Exploring the potential impact of advancements in generative AI (e.g., ChatGPT) on the interface design and the entire customer journey, from pre-purchase inquiries to post-adoption services.
Customer Features	(1) Focusing on customers with relatively low incomes, budgets, and financial literacy. (2) Exploring potential cultural and social influential factors.
Service Encounter Characteristics	(1) Evaluating customer post-adoption and long-term investment behaviors. (2) Examining unintended consequences and customers' experiences and behaviors in cases of service failures.
Laws, Ethics, and Regulations	(1) Unveiling the influence of institutional context (e.g.: ethics, regulations, and laws) in robo-advisory designs and service encounters. (2) Establishing the rules and criteria for developing regulatory framework for robo-advisors (3) Investigating the potential contributions of robo-advisors in customer protection, cybersecurity, and financial inclusion.
Research Methods and Perspectives	Shifting research focus towards interdisciplinary research and adoption of human-centered approaches: (1) Involving customers in robo-advisor design practices and iterative processes. (2) Investigating customer experiences by testing and evaluating existing robo-advisor information systems or services. (3) Understanding how the synergy of robot design, customer experience (e.g., perceptions in functional, social, and affective aspects), and customer features (e.g., income) jointly impacts robo-advisor acceptance and customer satisfaction.

Given the growing real-world use of robo-advisors, especially after the COVID-19 pandemic (Ben-David & Sade, 2020; Gan et al., 2021), there is a need to focus on customers' long-term use of robo-advisors and their post-adoption behaviors. This is vital because financial investment is a long-term commitment, and the performance of financial products can fluctuate daily. Long-term studies not only aid in customer retention management but also help measure customer satisfaction.

Moreover, existing research lacks in addressing service failures or unexpected customer behaviors. There is also a dearth of studies focusing on ethical and regulatory considerations in financial advisory services that go beyond AI-related issues in robo-advisor service encounters.

7. Conclusions

This article aims to systematically assess and synthesize the existing evidence and knowledge of service robots in financial advisory services, particularly frontline customer service encounters. To this end, 132 articles were reviewed and analyzed based on Belanche et al. (2020)'s framework on service robot implementation.

This review compensates for the lack of result-based analysis in previous robo-advisor review papers (Hentzen et al., 2022) and extends the domain focus from single disciplines(Torno & Metzler, 2021). We contribute to literature on service robots by contextualizing, refining, and extending the original framework by Belanche et al. (2020) and by developing a research agenda with critical perspectives. Moreover, the study yields practical and theoretical insights into artificial intelligence empowered financial advisory services. Particularly, practitioners may benefit from the integrative, state-of-the-art review, and the extended framework that provides clear-defined terms and evidence that can support their decision-making.

Furthermore, the review aligns with the human-centered AI approach, which calls for human control and human-centered design to enhance the explainability and transparency of autonomous service systems (Shneiderman, 2022).

Last, the review also has limitations. Some concepts discussed in several studies are not shown in the extended framework, for instance, the organizational challenges related to the implementation of robo-advisors (Rasiwala & Kohli, 2021), and subjective norms such as other people's opinions that can potentially affect individuals' attitudes towards robo-advisors (Belanche et al., 2019; Manrai & Gupta, 2023; Yeh et al., 2023). This is because they are not dominant themes within the reviewed literature. Still, these unexplored themes impact customer use of robo-advisors.

CRediT authorship contribution statement

Hui Zhu: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Olli Vigren:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Inga-Lill Söderberg:** Writing – review & editing, Validation, Supervision, Investigation.

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.

Data availability

See appendix

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2023.114494.

References

Adam, M., Toutaoui, J., Pfeuffer, N., & Hinz, O. (2020). *Investment decisions with robo-advisors: The role of anthropomorphism and personalized anchors in recommendations.* 27th European Conference on Information Systems - Information Systems for a Sharing Society, ECIS 2019. Scopus. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85087109501&partnerID=40&md5=6cdf3e42546628a3e8991152622edd11.

Al-Gasawneh, J. A., AL-Hawamleh, A. M., Alorfi, A., & Al-Rawashdeh, G. (2022). Moderating the role of the perceived security and endorsement on the relationship between per-ceived risk and intention to use the artificial intelligence in financial services. *International Journal of Data and Network Science, 6*(3), 743–752. 10.5267/j.ijdns.2022.3.007.

Au, C.-D., Klingenberger, L., Svoboda, M., & Frère, E. (2021). Business Model of Sustainable Robo-Advisors: Empirical Insights for Practical Implementation. *Sustainability, 13*(23), 13009. https://doi.org/10.3390/su132313009

Aw, E.-C.-X., Leong, L.-Y., Hew, J.-J., Rana, N. P., Tan, T. M., & Jee, T.-W. (2023). Counteracting dark sides of robo-advisors: Justice, privacy and intrusion considerations. *International Journal of Bank Marketing.* https://doi.org/10.1108/IJBM-10-2022-0439

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Baulkaran, V., & Jain, P. (2023). Who uses robo-advising and how? *Financial Review, 58*(1), 65–89. https://doi.org/10.1111/fire.12324

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial Management & Data Systems, 119*(7), 1411–1430. https://doi.org/10.1108/IMDS-08-2018-0368

Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2020). Service robot implementation: A theoretical framework and research agenda. *The Service Industries Journal, 40*(3–4), 203–225. https://doi.org/10.1080/02642069.2019.1672666

Belanche, D., Casaló, L. V., Flavián, M., & Loureiro, S. M. C. (2023). Benefit versus risk: A behavioral model for using robo-advisors. *The Service Industries Journal, 1–28*. https://doi.org/10.1080/02642069.2023.2176485

Belk, R. W., Belanche, D., & Flavián, C. (2023). Key concepts in artificial intelligence and technologies 4.0 in services. *Service Business, 17*(1), 1–9. https://doi.org/10.1007/s11628-023-00528-w

Beltramini, E. (2018). Human vulnerability and robo-advisory: An application of Coeckelbergh's vulnerability to the machine-human interface. *Baltic Journal of Management, 13*(2), 250–263. https://doi.org/10.1108/BJM-10-2017-0315

Ben David, D., Resheff, Y. S., & Tron, T. (2021). In *Explainable AI and Adoption of Financial Algorithmic Advisors: An Experimental Study* (pp. 390–400). and Society. https://doi.org/10.1145/3461702.3462565.

Ben-David, D., & Sade, O. (2020). Robo-advisor adoption, willingness to pay, and trust—Before and at the outbreak of the covid-19 pandemic. *Willingness to Pay, and Trust—Before and at the Outbreak of the COVID-19 Pandemic (July 2020)*.

Bertrand, A., Eagan, J. R., & Maxwell, W. (2023). In *Questioning the ability of feature-based explanations to empower non-experts in robo-advised financial decision-making* (pp. 943–958). and Transparency. https://doi.org/10.1145/3593013.3594053.

Bhatia, A., Chandani, A., Atiq, R., Mehta, M., & Divekar, R. (2021). Artificial intelligence in financial services: A qualitative research to discover robo-advisory services. *Qualitative Research in Financial Markets, 13*(5), 632–654. https://doi.org/10.1108/QRFM-10-2020-0199

Bhatia, A., Chandani, A., Divekar, R., Mehta, M., & Vijay, N. (2022). Digital innovation in wealth management landscape: The moderating role of robo advisors in behavioural biases and investment decision-making. *International Journal of Innovation Science, 14* (3/4), 693–712. https://doi.org/10.1108/IJIS-10-2020-0245

Blut, M., Heirati, N., & Schoefer, K. (2020). The dark side of customer participation: When customer participation in service co-development leads to role stress. *Journal of Service Research, 23*(2), 156–173.

Blut, M., & Wang, C. (2020). Technology readiness: A meta-analysis of conceptualizations of the construct and its impact on technology usage. *Journal of the Academy of Marketing Science, 48*, 649–669.

Boustani, N. M. (2022). Artificial intelligence impact on banks clients and employees in an Asian developing country. *Journal of Asia Business Studies, 16*(2), 267–278. https://doi.org/10.1108/JABS-09-2020-0376

Brenner, L., & Meyll, T. (2020). Robo-advisors: A substitute for human financial advice? *Journal of Behavioral and Experimental Finance, 25*, Article 100275. https://doi.org/10.1016/j.jbef.2020.100275

Breuer, T., Giorgana Macedo, G. R., Hartanto, R., Hochgeschwender, N., Holz, D., Hegger, F., Jin, Z., Müller, C., Paulus, J., & Reckhaus, M. (2012). Johnny: An autonomous service robot for domestic environments. *Journal of Intelligent & Robotic Systems, 66*, 245–272.

Brummer, C., & Yadav, Y. (2018). Fintech and the Innovation Trilemma. *THE GEORGETOWN LAW JOURNAL, 107*, 73.

Brunen, A.-C., & Laubach, O. (2021). Do sustainable consumers prefer socially responsible investments? A study among the users of robo advisors. *Journal of Banking & Finance, 106314*. https://doi.org/10.1016/j.jbankfin.2021.106314

Brunen, A.-C., & Laubach, O. (2022). Do sustainable consumers prefer socially responsible investments? A study among the users of robo advisors. *Journal of Banking & Finance, 136*, Article 106314. https://doi.org/10.1016/j.jbankfin.2021.106314

Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society*, *3*(1), 2053951715622512.

Čaić, M., Mahr, D., & Oderkerken-Schröder, G. (2019). Value of social robots in services: Social cognition perspective. *Journal of Services Marketing, 33*(4), 463–478. https://doi.org/10.1108/JSM-02-2018-0080

Canhoto, A. I. (2021). Leveraging machine learning in the global fight against money laundering and terrorism financing: An affordances perspective. *Journal of Business Research, 131*, 441–452.

Cecez-Kecmanovic, D. (2005). *Basic assumptions of the critical research perspectives in information systems* (pp. 19–46). Handbook of Critical Information Systems Research: Theory and Application.

Chang, Y., & Wang, R. (2023). Conservatives endorse Fintech? Individual regulatory focus attenuates the algorithm aversion effects in automated wealth management. *Computers in Human Behavior, 148*, Article 107872. https://doi.org/10.1016/j.chb.2023.107872

Chauhan, S., Akhtar, A., & Gupta, A. (2022). Customer experience in digital banking: A review and future research directions. *International Journal of Quality and Service Sciences.*

Cheng, X., Guo, F., Chen, J., Li, K., Zhang, Y., & Gao, P. (2019). Exploring the Trust Influencing Mechanism of Robo-Advisor Service: A Mixed Method Approach. *Sustainability, 11*(18), 4917. https://doi.org/10.3390/su11184917

Chhatwani, M. (2022). Does robo-advisory increase retirement worry? *A causal explanation. Managerial Finance, 48*(4), 611–628. https://doi.org/10.1108/MF-05-2021-0195

Chia, H. X. (2019). In Machines We Trust: Are Robo-Advisers More Trustworthy Than Human Financial Advisers? *Law, Technology and Humans, 129–141*. https://doi.org/10.5204/lthj.v1i0.1261

Choi, Y., Choi, M., Oh, M., & Kim, S. (2020). Service robots in hotels: Understanding the service quality perceptions of human-robot interaction. *Journal of Hospitality Marketing & Management, 29*(6), 613–635.

Crolic, C., Thomaz, F., Hadi, R., & Stephen, A. T. (2022). Blame the bot: Anthropomorphism and anger in customer–chatbot interactions. *Journal of Marketing, 86*(1), 132–148.

Crosman, P. (2019). January 2). *Can AI's 'black box' problem be solved?* American. *Banker*. https://www.americanbanker.com/news/can-ais-black-box-problem-be-solved.

Cui, Y. (Gina). (2022). Sophia Sophia tell me more, which is the most risk-free plan of all? AI anthropomorphism and risk aversion in financial decision-making. *International Journal of Bank Marketing*, *40*(6), 1133–1158. 10.1108/IJBM-09-2021-0451.

Day, M.-Y., Cheng, T.-K., & Li, J.-G. (2018). AI robo-advisor with big data analytics for financial services. *IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), 2018*, 1027–1031.

Deng, B., & Chau, M. (2021). *Anthropomorphized financial robo-advisors and investment advice-taking behavior*. 27th Annual Americas Conference on Information Systems, AMCIS 2021. Scopus. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85118625396&partnerID=40&md5=38fd0a0a65ac096324a9903636d13a2b.

Deo, S., & Sontakke, N. S. (2021). Usability, User Comprehension, and Perceptions of Explanations for Complex Decision Support Systems in Finance: A Robo-Advisory Use Case. *Computer, 54*(10), 38–48. https://doi.org/10.1109/MC.2021.3076851

Dhar, V. (2016, May 17). When to Trust Robots with Decisions, and When Not To. *Harvard Business Review*. https://hbr.org/2016/05/when-to-trust-robots-with-decisions-and-when-not-to.

D'Hondt, C., De Winne, R., Ghysels, E., & Raymond, S. (2020). Artificial Intelligence Alter Egos: Who might benefit from robo-investing? *Journal of Empirical Finance, 59*, 278–299. https://doi.org/10.1016/j.jempfin.2020.10.002

Di, X. (2022). From Prosperity to Deadlock: What's Wrong with Financial Supervision on Robo-Advisors in China. *Asian Journal of Law and Economics, 13*(2), 223–253. https://doi.org/10.1515/ajle-2022-0024

Dikmen, M., & Burns, C. (2022). The effects of domain knowledge on trust in explainable AI and task performance: A case of peer-to-peer lending. *International Journal of Human-Computer Studies, 162*, Article 102792. https://doi.org/10.1016/j.ijhcs.2022.102792

Dove, G., Balestra, M., Mann, D., & Nov, O. (2020). Good for the Many or Best for the Few?: A Dilemma in the Design of Algorithmic Advice. *Proceedings of the ACM on Human-Computer Interaction*, *4*(CSCW2), 1–22. 10.1145/3415239.

Falagas, M. E., Pitsouni, E. I., Malietzis, G. A., & Pappas, G. (2008). Comparison of PubMed, Scopus, Web of Science, and Google Scholar: Strengths and weaknesses. *The FASEB Journal, 22*(2), 338–342. https://doi.org/10.1096/fj.07-9492LSF

Faloon, M., & Scherer, B. (2017). *Individualization of Robo-Advice., 7*.

Fan, L., & Chatterjee, S. (2020). The Utilization of Robo-Advisors by Individual Investors: An Analysis Using Diffusion of Innovation and Information Search Frameworks. *Journal of Financial Counseling and Planning, 31*(1), 130–145. https://doi.org/10.1891/JFCP-18-00078

Faradynawati, I. A. A., & Söderberg, I.-L. (2022). Sustainable Investment Preferences among Robo-Advisor Clients. *Sustainability, 14*(19), 12636. https://doi.org/10.3390/su141912636

Figà-Talamanca, G., Tanzi, P. M., & D'Urzo, E. (2022). Robo-advisor acceptance: Do gender and generation matter? *PLOS ONE, 17*(6), e0269454.

Filiz, I., Judek, J. R., Lorenz, M., & Spiwoks, M. (2022). Algorithm Aversion as an Obstacle in the Establishment of Robo Advisors. *Journal of Risk and Financial Management, 15*(8), 353. https://doi.org/10.3390/jrfm15080353

Fisch, J. E., Labouré, M., & Turner, J. A. (2019). The Emergence of the Robo-Advisor. In J. E. In, M. L. Fisch, & J. A. Turner (Eds.), *The Disruptive Impact of FinTech on Retirement Systems* (pp. 13–37). Oxford University Press. https://doi.org/10.1093/oso/9780198845553.003.0002.

Fisk, R., Grove, S., Harris, L. C., Keeffe, D. A., Daunt, K. L., Russell-Bennett, R., & Wirtz, J. (2010). Customers behaving badly: A state of the art review, research agenda and implications for practitioners. *Journal of Services Marketing, 24*(6), 417–429.

Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2022). Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness. *Journal of Service Management, 33*(2), 293–320. https://doi.org/10.1108/JOSM-10-2020-0378

Forlizzi, J., & DiSalvo, C. (2006). Service robots in the domestic environment: A study of the roomba vacuum in the home. *Proceedings of the 1st ACM SIGCHI/SIGART Conference on Human-Robot Interaction*, 258–265.

Fulk, M., Grable, J. E., & Kruger, M. (2018). Who uses robo-advisory services, and who does not? *Financial Services Review, 27*(2), 173–188.

Gan, L. Y., Khan, M. T. I., & Liew, T. W. (2021). Understanding consumer's adoption of financial robo-advisors at the outbreak of the COVID-19 crisis in Malaysia. *FINANCIAL PLANNING REVIEW, 4*(3). https://doi.org/10.1002/cfp2.1127

Ganbold, O., Rose, A. M., Rose, J. M., & Rotaru, K. (2021). Increasing Reliance on Financial Advice with Avatars: The Effects of Competence and Complexity on Algorithm Aversion. *Journal of Information Systems*. https://doi.org/10.2308/ISYS-2021-002

Ge, R., Zheng, Z. (Eric), Tian, X., & Liao, L. (2021). Human–Robot Interaction: When Investors Adjust the Usage of Robo-Advisors in Peer-to-Peer Lending. *Information Systems Research*, *32*(3), 774–785. 10.1287/isre.2021.1009.

Gerlach, J. M., & Lutz, J. K. T. (2021). Digital financial advice solutions – Evidence on factors affecting the future usage intention and the moderating effect of experience. *Journal of Economics and Business, 117*, Scopus. https://doi.org/10.1016/j.jeconbus.2021.106009

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services. *Journal of Management Information Systems, 35*(1), 220–265. https://doi.org/10.1080/07421222.2018.1440766

Gopal, S., Gupta, P., & Minocha, A. (2023). Advancements in Fin-Tech and Security Challenges of Banking Industry. In *2023 4th International Conference on Intelligent Engineering and Management (ICIEM)* (pp. 1–6). https://doi.org/10.1109/ICIEM59379.2023.10165876

Haslem, J. A. (2010). The new reality of financial advisors and investors. *The Journal of Investing, 19*(4), 23–30.

Hayes, A. S. (2021). The active construction of passive investors: Robo advisors and algorithmic 'low-finance'. *Socio-Economic Review, 19*(1), 83–110. https://doi.org/10.1093/ser/mwz046

Hentzen, J. K., Hoffmann, A., Dolan, R., & Pala, E. (2022). Artificial intelligence in customer-facing financial services: A systematic literature review and agenda for future research. *International Journal of Bank Marketing, 40*(6), 1299–1336. https://doi.org/10.1108/IJBM-09-2021-0417

Hildebrand, C., & Bergner, A. (2021). Conversational robo advisors as surrogates of trust: Onboarding experience, firm perception, and consumer financial decision making. *Journal of the Academy of Marketing Science, 49*(4), 659–676. https://doi.org/10.1007/s11747-020-00753-z

Hilgert, M. A., Hogarth, J. M., & Beverly, S. G. (2003). Household financial management: The connection between knowledge and behavior. *Fed. Res. Bull., 89*, 309.

Hodge, F. D., Mendoza, K. I., & Sinha, R. K. (2021). The Effect of Humanizing Robo-Advisors on Investor Judgments*. *Contemporary Accounting Research, 38*(1), 770–792. https://doi.org/10.1111/1911-3846.12641

Hohenberger, C., Lee, C., & Coughlin, J. F. (2019). Acceptance of robo-advisors: Effects of financial experience, affective reactions, and self-enhancement motives. *FINANCIAL PLANNING REVIEW, 2*(2). https://doi.org/10.1002/cfp2.1047

Holland, J., Kingston, L., McCarthy, C., Armstrong, E., O'Dwyer, P., Merz, F., & McConnell, M. (2021). Service robots in the healthcare sector. *Robotics, 10*(1), 47.

Hong, X., Pan, L., Gong, Y., & Chen, Q. (2023). Robo-advisors and investment intention: A perspective of value-based adoption. *Information & Management, 60*(6), Article 103832. https://doi.org/10.1016/j.im.2023.103832

Hyun Baek, T., & Kim, M. (2023). Ai robo-advisor anthropomorphism: The impact of anthropomorphic appeals and regulatory focus on investment behaviors. *Journal of Business Research, 164*, Article 114039. https://doi.org/10.1016/j.jbusres.2023.114039

Iacurci, G. (2022). January 16). *Robo-advisors are growing in popularity. Can they really replace a human financial advisor? CNBC.* https://www.cnbc.com/2022/01/16/robo-advisors-are-gaining-popularity-can-they-replace-a-human-advisor.html.

Isaia, E., & Oggero, N. (2022). The potential use of robo-advisors among the young generation: Evidence from Italy. *Finance Research Letters, 48*, Article 103046. https://doi.org/10.1016/j.frl.2022.103046

Jung, D., Dorner, V., Glaser, F., & Morana, S. (2018). Robo-advisory. *Business & Information. Systems Engineering, 60*(1), 81–86.

Jung, D., Dorner, V., Weinhardt, C., & Pusmaz, H. (2018). Designing a robo-advisor for risk-averse, low-budget consumers. *Electronic Markets, 28*(3), 367–380. https://doi.org/10.1007/s12525-017-0279-9

Jung, D., Glaser, F., & Köpplin, W. (2019). Robo-Advisory: Opportunities and Risks for the Future of Financial Advisory. In V. Nissen (Ed.), *Advances in Consulting Research* (pp. 405–427). Springer International Publishing. https://doi.org/10.1007/978-3-319-95999-3_20.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Klink, R. R., Zhang, J. Q., & Athaide, G. A. (2020). Measuring customer experience management and its impact on financial performance. *European Journal of Marketing, 55*(3), 840–867.

Kraiwanit, T., Jangjarat, K., & Atcharanuwat, J. (2022). The acceptance of financial robo-advisors among investors: The emerging market study. *Journal of Governance and Regulation, 11*(2, special issue), 332–339. 10.22495/jgrv11i2siart12.

Kwon, D., Jeong, P., & Chung, D. (2022). An Empirical Study of Factors Influencing the Intention to Use Robo-Advisors. *Journal of Information & Knowledge Management, 21*(03), 2250039. https://doi.org/10.1142/S0219649222500393

Lee, J. (2020). Access to Finance for Artificial Intelligence Regulation in the Financial Services Industry. *European Business Organization Law Review, 21*(4), 731–757. https://doi.org/10.1007/s40804-020-00200-0

Lewis, D. R. (2018). The perils of overconfidence: Why many consumers fail to seek advice when they really should. *Journal of Financial Services Marketing, 23*(2), 104–111. https://doi.org/10.1057/s41264-018-0048-7

Lightbourne, J. (2017). Algorithms & Fiduciaries: Existing and Proposed Regulatory Approaches to Artificially Intelligent Financial Planners. *DUKE LAW JOURNAL, 67*, 29.

Lisauskiene, N., & Darskuviene, V. (2021). Linking the Robo-advisors Phenomenon and Behavioural Biases in Investment Management: An Interdisciplinary Literature Review and Research Agenda. *Organizations and Markets in Emerging Economies, 12*(2), 459–477. 10.15388/omee.2021.12.65.

Litterscheidt, R., & Streich, D. J. (2020). Financial education and digital asset management: What's in the black box? *Journal of Behavioral and Experimental Economics, 87*, Article 101573. https://doi.org/10.1016/j.socec.2020.101573

Liu, C., Yang, M., & Wen, M. (2023). Judge me on my losers: Do robo-advisors outperform human investors during the COVID-19 financial market crash? *Production and Operations Management, poms.14029*. https://doi.org/10.1111/poms.14029

Lobschat, L., Mueller, B., Eggers, F., Brandimarte, L., Diefenbach, S., Kroschke, M., & Wirtz, J. (2021). Corporate digital responsibility. *Journal of Business Research, 122*, 875–888.

Lourenço, C. J. S., Dellaert, B. G. C., & Donkers, B. (2020). Whose Algorithm Says So: The Relationships between Type of Firm, Perceptions of Trust and Expertise, and the Acceptance of Financial Robo-Advice. *Journal of Interactive Marketing, 49*(1), 107–124. https://doi.org/10.1016/j.intmar.2019.10.003

Lu, V. N., Wirtz, J., Kunz, W. H., Paluch, S., Gruber, T., Martins, A., & Patterson, P. G. (2020). Service robots, customers and service employees: What can we learn from the academic literature and where are the gaps? *Journal of Service Theory and Practice, 30*(3), 361–391. https://doi.org/10.1108/JSTP-04-2019-0088

Manrai, R., & Gupta, K. P. (2023). Investor's perceptions on artificial intelligence (AI) technology adoption in investment services in India. *Journal of Financial Services Marketing, 28*(1), 1–14. https://doi.org/10.1057/s41264-021-00134-9

Mbama, C. I., & Ezepue, P. O. (2018). Digital banking, customer experience and bank financial performance: UK customers' perceptions. *International Journal of Bank Marketing*.

McCartney, G., & McCartney, A. (2020). Rise of the machines: Towards a conceptual service-robot research framework for the hospitality and tourism industry. *International Journal of Contemporary Hospitality Management, 32*(12), 3835–3851.

McLeay, F., Osburg, V. S., Yoganathan, V., & Patterson, A. (2021). Replaced by a Robot: Service Implications in the Age of the Machine. *Journal of Service Research, 24*(1), 104–121.

Méndez Prado, S. M., Quishpillo Pilco, S. L., & Espin Parrales, W. S. (2022). Robo-Advisors: A perspective on the Latin American context. In *2022 6th International Conference on E-Commerce, E-Business and E-Government* (pp. 43–48). https://doi.org/10.1145/3537693.3537701

Met, İ., Kabukçu, D., Uzunoğulları, G., Soyalp, Ü., & Dakdevir, T. (2020). Transformation of business model in finance sector with artificial intelligence and robotic process automation. In *Digital Business Strategies in Blockchain Ecosystems: Transformational Design and Future of Global Business* (pp. 3–29).

Meyer, C., & Schwager, A. (2007). Understanding customer experience. *Harvard Business Review, 85*(2), 116.

Mezzanotte, F. E. (2020). An examination into the investor protection properties of robo-advisory services in Switzerland. *Capital Markets Law Journal, 15*(4), 489–508. https://doi.org/10.1093/cmlj/kmaa024

Mogaji, E., Soetan, T. O., & Kieu, T. A. (2021). The implications of artificial intelligence on the digital marketing of financial services to vulnerable customers. *Australasian Marketing Journal, 29*(3), 235–242. https://doi.org/10.1016/j.ausmj.2020.05.003

Mongeon, P., & Paul-Hus, A. (2016). The journal coverage of Web of Science and Scopus: A comparative analysis. *Scientometrics, 106*(1), 213–228. https://doi.org/10.1007/s11192-015-1765-5

Moore, D. L. (2003). Survey of financial literacy in Washington State: Knowledge, behavior, attitudes. *and experiences*. Washington State Department of Financial Institutions.

Morduch, J., & Schneider, R. (2017). *The financial diaries: How American families cope in a world of uncertainty*. Princeton University Press.

Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of Marketing, 58*(3), 20–38.

Nain, I., & Rajan, S. (2023). Algorithms for better decision-making: A qualitative study exploring the landscape of robo-advisors in India. *Managerial Finance*. https://doi.org/10.1108/MF-01-2023-0055

Naveed, S., Stevens, G., & Kern, D.-R. (n.d.). *Explainable Robo-Advisors: Empirical Investigations to Specify and Evaluate a User-Centric Taxonomy of Explanations in the Financial Domain*.

Northey, G., Hunter, V., Mulcahy, R., Choong, K., & Mehmet, M. (2022). Man vs machine: How artificial intelligence in banking influences consumer belief in financial advice. *International Journal of Bank Marketing, 40*(6), 1182–1199. https://doi.org/10.1108/IJBM-09-2021-0439

Nourallah, M. (2023). One size does not fit all: Young retail investors' initial trust in financial robo-advisors. *Journal of Business Research, 156*, Article 113470. https://doi.org/10.1016/j.jbusres.2022.113470

Nourallah, M., Öhman, P., & Amin, M. (2023). No trust, no use: How young retail investors build initial trust in financial robo-advisors. *Journal of Financial Reporting and Accounting, 21*(1), 60–82. https://doi.org/10.1108/JFRA-12-2021-0451

Oehler, A., Horn, M., & Wendt, S. (2022). Investor Characteristics and their Impact on the Decision to use a Robo-advisor. *Journal of Financial Services Research, 62*(1–2), 91–125. https://doi.org/10.1007/s10693-021-00367-8

Ostrom, A. L., Fotheringham, D., & Bitner, M. J. (2019). Customer acceptance of AI in service encounters: Understanding antecedents and consequences. *Handbook of Service Science, II*, 77–103.

Paterson, J. M. (2021). Making robo-advisers careful? Duties of care in providing automated financial advice to consumers. *Law and Financial Markets Review, 15*(3–4), 278–295. https://doi.org/10.1080/17521440.2023.2196027

Paul, J., Merchant, A., Dwivedi, Y. K., & Rose, G. (2021). Writing an impactful review article: What do we know and what do we need to know? *Journal of Business Research, 133*, 337–340. https://doi.org/10.1016/j.jbusres.2021.05.005

Piehlmaier, D. M. (2022). Overconfidence and the adoption of robo-advice: Why overconfident investors drive the expansion of automated financial advice. *Financial Innovation, 8*(1), 14. https://doi.org/10.1186/s40854-021-00324-3

Pinillos, R., Marcos, S., Feliz, R., Zalama, E., & Gómez-García-Bermejo, J. (2016). Long-term assessment of a service robot in a hotel environment. *Robotics and Autonomous Systems, 79*, 40–57.

Piotrowski, D. (2022). Consumer perceived ethicality of banks in the era of digitalisation: The case of Poland. *Economics and Business Review, 8*(1), 25.

Pitardi, V., & Marriott, H. R. (2021). Alexa, she's not human but… Unveiling the drivers of consumers' trust in voice-based artificial intelligence. *Psychology & Marketing, 38*(4), 626–642.

Rao, A. S., & Verweij, G. (2017). *Sizing the prize: What's the real value of AI for your business and how can you capitalise* (pp. 1–30). PwC: PwC Publication.

Rasiwala, F. S., & Kohli, B. (2021). Artificial Intelligence in FinTech: Understanding Stakeholders Perception on Innovation, Disruption, and Transformation in Finance. *International Journal of Business Intelligence Research, 12*(1), 48–65. https://doi.org/10.4018/IJBIR.20210101.oa3

Riitsalu, L., & Uusberg, A. (2021). To double, quadruple, or keep? Semi-automated service increases micro-investments. *Journal of Behavioral and Experimental Economics, 95*, Article 101774. https://doi.org/10.1016/j.socec.2021.101774

Robinson, S., Orsingher, C., Alkire, L., De Keyser, A., Giebelhausen, M., Papamichail, K. N., Shams, P., & Temerak, M. S. (2020). Frontline encounters of the AI kind: An evolved service encounter framework. *Journal of Business Research, 116*, 366–376. https://doi.org/10.1016/j.jbusres.2019.08.038

Roy, N., Baltus, G., Fox, D., Gemperle, F., Goetz, J., Hirsch, T., Margaritis, D., Montemerlo, M., Pineau, J., & Schulte, J. (2000). Towards personal service robots for the elderly. *Workshop on Interactive Robots and Entertainment (WIRE 2000)*, *25*, 184.

Ryoo, Y., Jeon, Y. A., & Kim, W. (2024). The blame shift: Robot service failures hold service firms more accountable. *Journal of Business Research, 171*, Article 114360.

Sakai, T., & Nagai, T. (2022). Explainable autonomous robots: A survey and perspective. *Advanced Robotics, 36*(5–6), 219–238.

Salo, M., & Haapio, H. (2017). Robo-Advisors and Investors: Enhancing Human-Robot Interaction Through Information Design. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2937821

Salo-Lahti, M. (2022). Good or Bad Robots? *Responsible Robo-Advising. European Business Law Review, 33*(5).

Scherer, B., & Lehner, S. (2023). Trust me, I am a Robo-advisor. *Journal of Asset Management, 24*(2), 85–96. https://doi.org/10.1057/s41260-022-00284-y

Seiler, V., & Fanenbruck, K. M. (2021). Acceptance of digital investment solutions: The case of robo advisory in Germany. *Research in International Business and Finance, 58*, Scopus. https://doi.org/10.1016/j.ribaf.2021.101490

Shan, S., Umar, M., & Mirza, N. (2022). Can robo advisors expedite carbon transitions? Evidence from automated funds. *Technological Forecasting and Social Change, 180*, Article 121694. https://doi.org/10.1016/j.techfore.2022.121694

Shneiderman, B. (2022). *Human-Centered AI* (1st ed.). Oxford University Press. 10.1093/oso/9780192845290.001.0001.

Snihovyi, O., Kobets, V., & Ivanov, O. (2019). *Implementation of Robo-Advisor Services for Different Risk Attitude Investment Decisions Using Machine Learning Techniques* (V. Ermolayev, M. C. Suárez-Figueroa, V. Yakovyna, H. C. Mayr, M. Nikitchenko, & A. Spivakovsky, Trans.). 298–321.

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research, 104*, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

Söderberg, I. L. (2013). Relationships between advisor characteristics and consumer perceptions. *International Journal of Bank Marketing*.

Steennot, R. (2022). Robo-advisory services and investor protection. *Law and Financial Markets Review, 15*(3–4), 262–277. https://doi.org/10.1080/17521440.2022.2153610

Tan, G. K. S. (2020). Robo-advisors and the financialization of lay investors. *Geoforum, 117*, 46–60. https://doi.org/10.1016/j.geoforum.2020.09.004

Tertilt, M., & Scholz, P. (2018). To advise, or not to advise—How robo-advisors evaluate the risk preferences of private investors. *The Journal of Wealth Management, 21*(2), 70–84.

Thekkethil, M. S., Shukla, V. K., Beena, F., & Chopra, A. (2021). Robotic process automation in banking and finance sector for loan processing and fraud detection. In *2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO)* (pp. 1–6).

Tiberius, V., Gojowy, R., & Dabić, M. (2022). Forecasting the future of robo advisory: A three-stage Delphi study on economic, technological, and societal implications. *Technological Forecasting and Social Change, 182*, Article 121824. https://doi.org/10.1016/j.techfore.2022.121824

Tokic, D. (2018). BlackRock Robo-Advisor 4.0: When artificial intelligence replaces human discretion. *Strategic Change, 27*(4), 285–290. https://doi.org/10.1002/jsc.2201

Torno, A., & Metzler, D. R. (2021). *Robo-What?, Robo-Why?, Robo-How? – A Systematic Literature Review of Robo-Advice*. *PACIS*, 92.

Tsai, W.-H.-S., Liu, Y., & Chuan, C.-H. (2021). How chatbots' social presence communication enhances consumer engagement: The mediating role of parasocial interaction and dialogue. *Journal of Research in Interactive Marketing, 15*(3), 460–482.

Turner, J. A., & Klein, B. W. (2021). Improving on Defaults: Helping Pension Participants Manage Financial Market Risk in Target Date Funds. *Risks, 9*(4), 79. https://doi.org/10.3390/risks9040079

von Walter, B., Kremmel, D., & Jäger, B. (2022). The impact of lay beliefs about AI on adoption of algorithmic advice. *Marketing Letters, 33*(1), 143–155. https://doi.org/10.1007/s11002-021-09589-1

Waliszewski, K., & Warchlewska, A. (2020). Attitudes towards artificial intligence in the area of personal financial planning: A case study of selected countries. *Entrepreneurship and Sustainability Issues, 8*(2), 399–420. https://doi.org/10.9770/jesi.2020.8.2(24)

Walker, J. L. (1995). Service encounter satisfaction: Conceptualized. *Journal of Services Marketing, 9*(1), 5–14. https://doi.org/10.1108/08876049510079844

Walsh, D., & Downe, S. (2005). Meta-synthesis method for qualitative research: A literature review. *Journal of Advanced Nursing, 50*(2), 204–211.

Wirtz, J., Hartley, N., Kunz, W. H., Tarbit, J., & Ford, J. (2021). Corporate digital responsibility at the dawn of the digital service revolution. *Available at SSRN 3806235*.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management, 29*(5), 907–931.

Xia, Y., Chen, Y., Luo, H., Yang, Y., & Wang, X. (2022). In *Research and Improvement on the Development of Robo-Advisor: Present and Prospect* (pp. 172–178). https://doi.org/10.1145/3531232.3531257

Xiao, L., & Kumar, V. (2021). Robotics for customer service: A useful complement or an ultimate substitute? *Journal of Service Research, 24*(1), 9–29.

Yeh, H.-C., Yu, M.-C., Liu, C.-H., & Huang, C.-I. (2023). Robo-advisor based on unified theory of acceptance and use of technology. *Asia Pacific Journal of Marketing and Logistics, 35*(4), 962–979. https://doi.org/10.1108/APJML-07-2021-0493

Zhu, H., Pysander, E.-L.-S., & Söderberg, I.-L. (2023). *Not transparent and incomprehensible: A qualitative user study of an AI-empowered financial advisory system* (p. 100041). Data and Information Management.

Zunzunegui, F. (2022). Robo-Advice as a Digital Finance Platform. *European Company and Financial Law Review, 19*(2), 272–304. https://doi.org/10.1515/ecfr-2022-0011

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