Implications of AI-based robo-advisory for private banking investment advisory

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Abstract

Purpose – AI-based robo-advisory (RA) represents a FinTech application that is already replacing retail investment advisors. In private banking (PB), clients also increasingly expect service provision across different digital channels, but with a higher degree of personalization. Hence, the present study investigates the impact of intelligent RA on the PB investment advisory process to derive both process (re)design knowledge and strategic guidance for artificial intelligence (AI) usage for PB investment advisory.

Design/methodology/approach – The present study applies an AI process impact analysis approach by decomposing AI-based RA into three AI application types: conversational agent, customer segmentation and predictive analytics. The analysis results along a reference PB investment advisory process reveal sub-process transformations which are applied for process redesign integrating AI.

Findings – The study results imply that AI systems (1) enable seamless client journeys, (2) increase advisor flexibility, (3) support the client–advisor relationship by applying an omnichannel approach and (4) demand advisor skills to be augmented with technical and statistical knowledge.

Originality/value – The research study contributes (1) an AI process impact analysis approach, (2) derives process (re)design knowledge for AI deployment and (3) develops strategic guidance for AI usage in PB investment advisory.

Keywords Artificial intelligence, Robo-advisory, Financial services, Private banking

Paper type Research paper

Introduction

Robo-advisory (RA) is a widely recognized trend in the financial industry and the FinTech sector. The term "FinTech" represents the abbreviation of "financial technology" and describes both innovative IT-based financial solutions as well as companies offering such solutions (Jung, Dorner, Glaser, & Morana, 2018a). RA is considered as a business model archetype that represents a decision support system from a technological perspective and a personal assistant from a product offering perspective (Eickhoff, Muntermann, & Weinrich, 2017). With RA offering low fees and minimum deposit requirements, private banking (PB) client advisors are facing increased competition (von Martens & Schildbach, 2019). Besides, the number of global RA users is expected to be half a billion by 2025 accompanied by changes in client behavior and expectations (Statista, 2021a). Artificial

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intelligence (AI) may not only boost RA adoption as well as their assets under management, but AI-based RA application types could also decrease transaction costs and support investment advisors to understand client needs (Renaux, Rudnicki, Beniere, & Lorain, 2019; Brodski, 2019). Wealth managers and private banks need to develop concepts integrating AI-based solutions within their value chain since especially young, technology-savvy clients expect digital services as well as personalized offerings and advisor contact (Kothari & Berry, 2021; Sachse, Puschmann, & Alt, 2012). According to a study by Accenture (2018), 63% of the high-net-worth individuals (HNWIs) are highly interested in individual journeys across digital channels and more than half of HNWIs would leave their private bank if no integrated and seamless channels are available. Since the technological possibilities driven by AI indicate the PB client advisor no longer to be the main client contact and PB profitability is decreasing, private banks need to redesign investment advisory implementing AI-based solutions such as intelligent RA and find a balance between machine- and human-centered client interaction (Moulliet, Majonek, Stolzenbach, & Völker, 2016a). While retail banks already started integrating intelligent systems, private banks lag the development and are still evaluating or testing the integration of AI applications in the investment advisory process (Forbes Insights, 2019). The academic literature is mainly concerned with the design of AI-based RA (e.g. Jung *et al.*, 2018a) and behavioral investigations (e.g. Wang, 2020) with a research gap regarding the processual redesign and business impact of AI-based RA application types, especially on PB investment advisory. The process coverage by AI-based systems as well as the application potentials resulting from media discontinuities in the process have hardly been considered so far (Dietzmann, Heines, & Alt, 2020). Hence, the present research paper examines two research questions (RQs):

RQ1. What is the processual impact of AI-based RA on PB investment advisory?

RQ2. What are the implications for AI-based PB investment advisory?

The RQs are addressed by deploying process-related and AI-based RA characteristics on the PB investment advisory process developed by Nueesch, Zerndt, Alt, and Ferretti (2016). The two main goals of the study are to derive knowledge about (1) the process influence of AI-based characteristics and (2) process redesign integrating AI. The remainder of the paper is as follows: The next section lays the foundations of AI-based RA, the AI application types and existing research. Section 3 presents the methodology and characterizes the PB investment advisory process; section 4 contains the iterative development of the process redesign and the evaluation. Section 5 discusses the implications, limitations and further research opportunities. Section 6 concludes the paper.

Existing research on robo-advisory

Emergence of AI-based robo-advisory

The origins of the RA business model date back to the year 2008, when US FinTech companies Wealthfront and Betterment were founded (Fisch, Labouré, & Turner, 2019) and developed innovative solutions for advisory processes, which were not yet associated with automation and the term "robo" for "robot" (Alt & Puschmann, 2012). With the robo-advisors "vaamo", "moneyfarm" and "quirion", similar businesses gained popularity in Germany since 2014, being the second largest European FinTech market with 25 robo-advisors following the UK (Alt, Beck, & Smits, 2018; von Martens & Schildbach, 2019). The emergence of robo-supported business models was fueled by both a loss of confidence in actively managed funds following the financial crisis in 2008 and new technical possibilities (Poterba & Shoven, 2002). In contrast to traditional banks, RA providers offer capital market access to formerly unbanked customers via excange traded funds (ETF) investments starting from one Euro as minimum investment or monthly savings rate (Hoelscher & Nelde, 2018). The business models focus on the young and technology-savvy generation with low, but potentially growing incomes, which in 2016 was only considered serious competition by six to seven percent of 134 German asset managers participating in a study (Sironi, 2016; Webersinke, 2017). This impression changed with RA assets under management in Germany having more than tenfold from EUR 756m in 2017 to EUR 8.068bn in 2020 and are expected to reach EUR 30.515bn in 2025 (Statista, 2021b). The estimates are also driven by the cooperation with banks and asset managers implementing RA solutions. Besides the "white label solution" strategy, RA providers have developed the "platform solution" and the "software-as-a-service" (SaaS) strategy. The "white label solution" is considered the most uncomplicated variant since the RA simply offers its complete service under the name of the contracting partner. The banks' risk of this strategy is a possible migration of customers to RA, the advantages are low implementation and maintenance costs. In the two other cooperation forms, RAs act as pure IT service providers implementing the bank's products and processes digitally. Thus, the bank's investment advisor remains with these two solutions for queries based on product knowledge. The two latter strategies differ by the aspect that in the platform solution, the RA can be assigned the tasks of processing and custody account management, whereas in the SaaS solution all nontechnical tasks remain with the bank (Schabicki, Quint, & Schroeder, 2020). Investment advisory digitization triggers transformation along two dimensions. The first one is the physical dimension, i.e. the face-to-face customer–bank communication getting replaced by digital devices such as smartphones and tablets (Cocca, 2016; Nueesch *et al.*, 2016). In the second dimension, novel technologies transform and automate advisory content creation, thereby shifting the focus from human- to algorithm-based investment advice. The first digital continuation of the traditional "human advisory" archetype represents a converging online and offline channel combination (Nüesch, Alt, & Puschmann, 2015). Although human advisory still dominates customer relationships in this archetype, clients may change between digital channels like e-mails, video telephony or chats. From an evolutionary viewpoint, RA archetype contains four generations with the first representing a simple tool displaying investment options based on an online questionnaire. The second generation comprises investment platforms enabling customers to invest in ready-made investment funds. Asset managers execute the purchase orders, prepare the asset allocations and monitor the entire process. The third evolutionary stage is characterized by rule-based algorithms automatically proposing investments and executing portfolio adjustments. RA 4.0 includes self-learning algorithms being capable of investing and portfolio rebalancing driven by advances in AI (Moulliet *et al.*, 2016a; Perrin & Roncalli, 2020). Intelligent conversational agents (CA) guide users through business processes while other AI components like predictive Analytics (PA) or intelligent customer segmentation (CS) have an impact on the quality and depth of advisory content (Law & Chung, 2020; Beck, 2020).

AI-based robo-advisory application types

AI-based RA can be decomposed into AI application types that have significantly driven its evolution. An application type refers to a software cluster solving similar problems within a specific task environment such as recognizing speech, playing chess or driving cars (Russell & Norvig, 2016; Boobier, 2020). An advanced RA is composed of many such application types to address the high decision-making complexity in investment advisory. Based on the three types of AI presented by Davenport and Ronanki (2018), the following AI-based RA application types could be identified: intelligent CA (Day, Lin, & Chen, 2018;

Hildebrand & Bergner, 2021), intelligent CS (Tertilt & Scholz, 2018; Xue, Zhu, Liu, & Yin, 2018) and PA (Day & Lin, 2019; Gu, Hsieh, Wu, Chang, & Ho, 2019). The characteristics of each are the following.

Intelligent CA: The connection of AI and intelligent conversational systems processing natural language enables automated interactions between banks and clients via text-based chatbots and audio-based voice assistants (Day *et al.*, 2018; Liao, Ma, He, Hong, & Chua, 2018). This form of communication is primarily used for customer inquiries relieving the cost-intensive front office (Crosman, 2018). According to the Financial Stability Board (Schindler *et al.*, 2017) the range of tasks performed by chatbots and voice assistants in the financial industry is still modest and limited to routine and simple activities. However, due to recent technological advances in machine learning, a generation of intelligent CAs is evolving (Li *et al.*, 2019; Yan, 2018). A significant advantage over other interaction channels arises primarily from the high degree of mobility. A CA can typically be implemented across multiple devices and applications so that the customer can interact with the bank regardless of time and place. For example, the financial services provider Wells Fargo uses Facebook's Messenger service to automatically answer simple customer queries (Burnett, 2017).

Intelligent CS: Banks are increasingly replacing rigid and generalized segmentation approaches with individual profiling addressing the immense complexity and multi-layered nature of customer needs as proposed by Khadivizand *et al.* (2020). With the help of AI-based CS, RAs automatically divide the market and its clientele into meaningful (micro) segments by assessing risk preferences or even analyzing their behavior such as answer switching while filling out a digital questionnaire (Tertilt & Scholz, 2018; Tsiptsis and Chorianopoulos, 2011; McDonald, 2019). Through this process, buyer groups may be identified to determine their specific characteristics and to predict the individual risk (Beck, 2020). Kilic, Dolata, and Schwabe (2017) find that client profiling should not necessarily be carried out purely digitally, but that joint profiling is much more accepted by clients. If the intelligent system correctly identifies the customer segment based on the joint profiling, risk-accurate investment solutions can be offered, underlining that intelligent financial innovations are advantageous for both customers and bank risk-taking (Dietzmann & Alt, 2019).

Predictive analytics: PA is an AI application type that helps identifying patterns from a vast amount of data to make predictions about business-relevant content (Joshi, Lavanchy, & Stehli, 2018). In doing so, algorithms can identify parametric and nonparametric relationships that are mostly imperceptible to humans (LeCun, Bengio, & Hinton, 2015). In many cases, the datasets available to organizations are too large for human experts and therefore, AI-based data processing is effectively supporting the generation of market or stock price predictions (Day *et al.*, 2018; Althelaya, El-Alfy, & Mohammed, 2018). The underlying algorithms often process input data such as macroeconomic data and company-related financial information (Wang, Liu, Yang, & Huang, 2019), social network relationship data (Xue *et al.*, 2018) or Twitter sentiment (Oliveira, Cortez, & Areal, 2017). A benefit of PA is the absence of subjective influences, mitigated by the high degree of diversified information and AI model selection, e.g. in sentiment-based predictions.

Robo-advisory in information systems research

RA has already received some attention in the information systems (IS) literature. Jung *et al.* (2018a) observe "interface design" and "behavior" as the two main research streams addressed by RA research. Most scholars focus on interface design in connection with (1) transparency and trust (Jung *et al.*, 2018a; Kilic *et al.*, 2015, 2017; Mesbah, Tauchert, Olt, & Buxmann, 2019; Rühr, 2020), (2) design approaches such as anthropomorphism (Morana, Gnewuch, Jung, & Granig, 2020; Adam, Toutaoui, Pfeuffer, & Hinz, 2019), nudging (Jung & Weinhardt, 2018) as well as user control (Rühr, Berger, & Hess, 2019) and (3) the change from display-to voice-based RA (Ostern, Schöler, & Moormann, 2020). The “behavior” research stream developed further by evaluating RA adoption, in which scholars investigate adoption determinants and barriers (Wang, 2020; Bruckes, Westmattelmann, Oldeweme, & Schewe, 2019), trust-influencing factors (Guo, Cheng, & Zhang, 2019), users’ utilization of robo-advice (Tauchert & Mesbah, 2019), RA user characteristics (Woodyard & Grable, 2018; Fulk, Grable, Watkins, & Kruger, 2018) and user attitudes encouraging and discouraging RA adoption (Belanche, Casaló, & Flavián, 2019). In addition, a third stream contains IS literature focusing on the business process impact and process redesign of and by RA as well as its effect on human-based financial advisory. The results of a qualitative case study by Coombs and Redman (2018) imply to augment the human advisor with RA since financial investment is an emotional process and the RA’s ability to show empathy are limited (Jung, Glaser, & Köpplin, 2019). The RA’s lack of emotionality is even considered to improve financial decision-making – and thus achieve the performance of professional investors, who regularly outperform retail investors (Kinniry & DiJoseph, 2014). Nevertheless, RA may be vulnerable to conflicts of interest because of their affiliation with brokers, clearing firms, etc., which in turn may lead to higher prices (Fein, 2015). It has also been observed that RAs feature difficulties in the evaluation of client risk tolerance and provision of highly personalized services, which is important in PB (Jung *et al.*, 2019). Nueesch, Puschmann, and Alt (2014) address the aspect of human augmentation with tablet-based applications in the PB investment advisory process. The findings imply a redesign of the advisory process and provide first indications on the impact AI-based RA application types may have when augmenting a human financial advisor. In a further study on tablet-based financial advisory, Nueesch *et al.* (2016) proposed tablet-supported PB investment advisory process variants.

Conceptualization

Methodology

The research gap is addressed through the application of design science research (DSR) according to Hevner, March, Park, and Ram (2004). DSR was applied since the present study develops practically utilizable results, which is one of DSR’s main goals (Winter, 2008). Furthermore, the research approach follows the design cycles proposed by Peffers, Tuunanen, Rothenberger, and Chatterjee (2007) to ensure rigor and relevance. First, the problem is identified through a literature review and the study objectives are defined (Webster & Watson, 2002). The design and development phase contains the process characterization, derivation of process-relevant RA characteristics and an impact analysis of the AI-based RA application types CA, CS and PA on the PB investment advisory process. The demonstration is presented by the re-designed investment advisory process, including an integration of the three AI-based application types. The AI potentials for process redesign were discussed in 10 semi-structured PB expert interviews and the evaluation was conducted in four separate semi-structured interviews with both PB and technology experts. Finally, the design knowledge is presented by three implications for future AI-based PB investment advisory (Figure 1).

Characterization of the private banking investment advisory process

The traditional investment advisory process is an integral part of a private bank’s overall sales process, which encompasses the client–bank interface. To create an adequate understanding of the tasks connected with investment advisory, this paper applies a PB advisory process, which was proposed by Nueesch *et al.* (2016) and employed in an impact analysis of tablets onto bank advisory. The process represents the traditional end-to-end investment advisory process, which is carried out by a human advisor being separated into six process steps: (1) initiation, (2) profiling, (3) concept, (4) offer, (5) implementation and (6) maintenance. The process steps are divided into 26 sub-processes, which are the object of investigation for the impact analysis of the RA-related AI application types (Figure 2).

Process-relevant robo-advisory characteristics

A structured literature review following Webster and Watson (2002) was conducted to identify process-relevant RA characteristics for the subsequent iterative process redesign. The search string ("robo advice" OR "robo advisor" OR "robo advisory") was applied to title, abstract and keywords for the databases AISeL, IEEE Xplore, ACM DL and Springer Link database including a backward-forward search. The literature search resulted in a total set of 617 documents, which were analyzed for relevance to the RQs. More precisely, the existing body of knowledge was screened for articles containing RA characteristics, which are relevant in the context of the investment advisory process. Inappropriate research papers and duplicates were excluded during this process. Another full-text screening resulted in 19 articles that were reviewed in detail by two of the authors. The authors extracted seven RA characteristics, which are considered to manifest the impact of RA within a process (Table 1): *Accessibility*, *automation*, *availability*, *efficiency*, *standardization*, *transparency* and *usability* are considered to manifest the impact of RA within a process. During the impact analysis of the subsequent iterative process redesign of the present study, the seven process-relevant RA characteristics are applied on each of the investment advisory sub-processes through the three AI application types. The RA characteristics and corresponding scientific literature are shown in Table 1.

Quantifying the fit of the three AI application types in processes, the indicative correlations from Figure 3 are applied during the impact analysis. The correlation scale indicates the extent to which the respective AI application type has the potential to introduce the respective RA characteristic into a process and consequently improve it. The assignment of AI applications and RA characteristics was derived during the expert interviews. The interfaces of both axes show either a very high, high, moderate, low, very low or no correlation. The higher the sum of correlations per application type, the greater the effects on the respective sub-processes to be analyzed in chapter 4.1. Therefore, it is expected that the intelligent CA has the highest impact on the process, also because of its high relevance for client interaction, while the impact of CS and PA is expected to have less direct and more indirect impact on the process through the intelligent CA application.

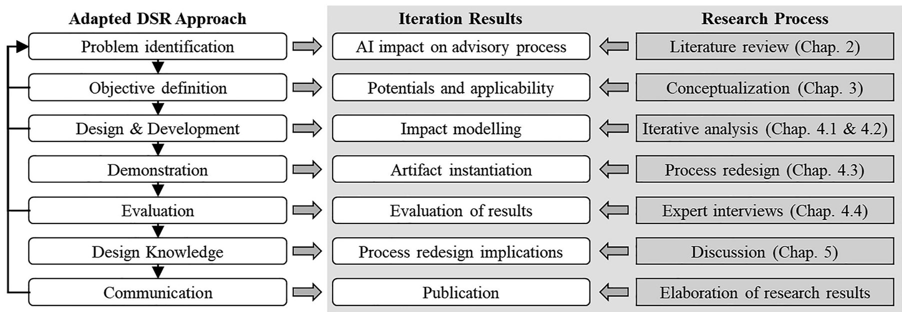

Figure 1.
Research design cycles and iterative results based on Peffers *et al.* (2007)

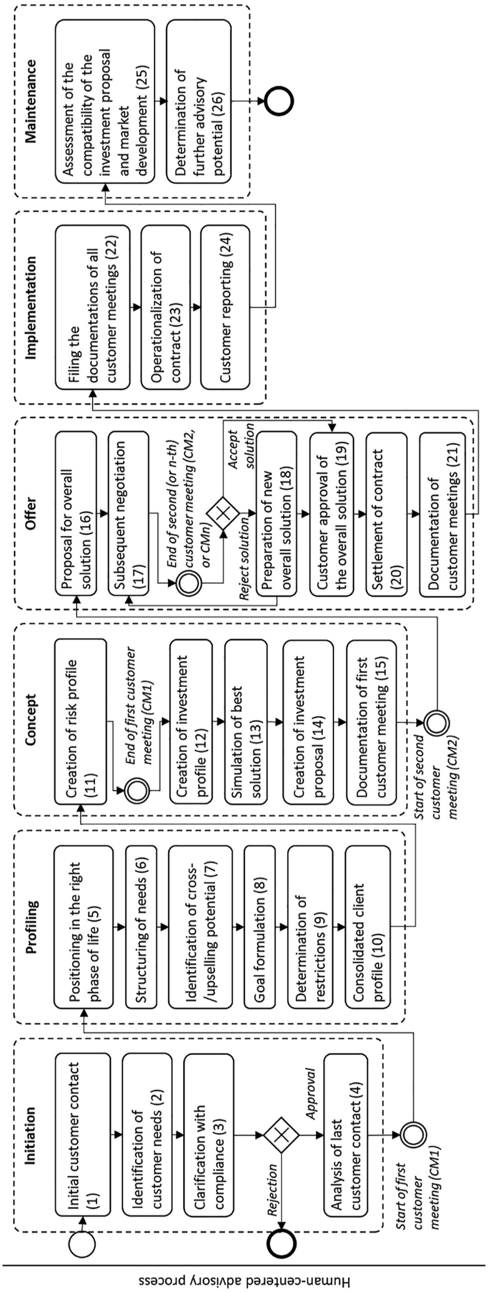

Figure 2.
The private banking investment advisory process based on Nueesch *et al.* (2016)

Robo-advisory characteristic	Explanation	References
Accessibility	A characteristic feature of robo-advisors is the ease of access to the service. In principle, this also enables customers with low assets to use the service of an asset management company	Becchi *et al.* (2018), Jung *et al.* (2018a), Kaya *et al.* (2017), O'Keefe *et al.* (2016), Ruf *et al.* (2015)
Automation	Automated activities by the robo-advisor allow the overall advisory process but also particular sub-processes to be executed without human intervention	Becchi *et al.* (2018), D'Acunto *et al.* (2019), Fein (2015), Fisch *et al.* (2019), Gold and Kursh (2017), Jung *et al.* (2018a), Kaya *et al.* (2017), Moulliet *et al.* (2016a), Moulliet, Stolzenbach, Bein, and Wagner (2016b), Rühr (2020), Sironi (2016)
Availability	The advisory process can be accessed at any time and from any location, provided the user has an internet-enabled device and the robo-advisor is not affected by server problems	Becchi *et al.* (2018), Fisch *et al.* (2019), Jung *et al.* (2018a), Moulliet *et al.* (2016a), Panebianco and Folcia (2016), Singh and Kaur (2017)
Efficiency	The robo-advisor executes the individual sub-processes or activities within the advisory process in less time and at lower costs compared to the bank advisor	D'Acunto *et al.* (2019), Fisch *et al.* (2019), Gold and Kursh (2017), Jung, Dorner, Weinhardt, and Pusmaz (2018b), Kaya *et al.* (2017), Moulliet *et al.* (2016a), Panebianco and Folcia (2016), Singh and Kaur (2017), Sironi (2016), Tauchert and Mesbah (2019)
Standardization	Some process steps are unchangeable and standardized in their sequence and the activities they contain. For this reason, every customer can always be guaranteed consistent quality and exclusion of human advisory errors	Fisch *et al.* (2019), Jung *et al.* (2018a), Kaya *et al.* (2017), Singh and Kaur (2017)
Transparency	Transparent robo-advisors allow each step within the end-to-end process to be rationally and logically justified creating trust toward the user	Climescu *et al.* (2021), D'Acunto *et al.* (2019), Gold and Kursh (2017), Jung *et al.* (2018a, b), Kaya *et al.* (2017), Moulliet *et al.* (2016a), O'Keefe *et al.* (2016), Panebianco and Folcia (2016), Ruf *et al.* (2015), Rühr (2020), Singh and Kaur (2017), Tauchert and Mesbah (2019)
Usability	Content is presented in a modern way and customers are actively involved in the process, in which, e.g. they must make investment decisions in a playful way based on sample situations and are thus involved in determining their risk attitude	Becchi *et al.* (2018), D'Acunto *et al.* (2019), Fisch *et al.* (2019), Jung *et al.* (2018b), Kaya *et al.* (2017), O'Keefe *et al.* (2016), Panebianco and Folcia (2016), Ruf *et al.* (2015), Singh and Kaur (2017), Sironi (2016)

Table 1.
Process-relevant RA characteristics

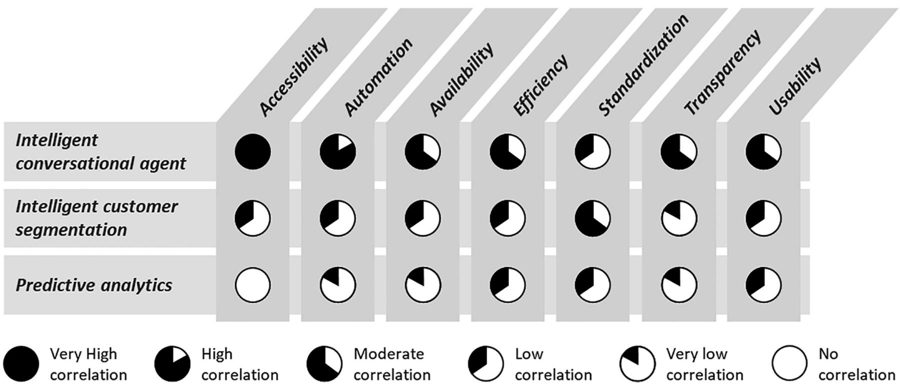

Figure 3.
Indicative correlation of AI application process optimization potentials

Iterative impact analysis

Impact on sub-processes

The impact analysis is conducted by applying the three AI-based RA application types CA, CS and PA with their individual causative characteristics onto the PB investment advisory process. The analysis of each process step results in a transformation, which is expressed by either a

(1) merger (due to AI application functionalities addressing process steps at the same time)

(2) elimination (process steps that, due to AI application functionalities, become so inherent to other process steps that they become "invisible")

(3) shifting (execution of the process step elsewhere in the process)

(4) or acceleration (faster execution of the process step due to AI application functionalities)

of sub-processes providing indications for process redesign which are based on the condition statements of Netjes *et al.* (2007). Subsequently, each AI-based application type and corresponding transformations are applied for process re-design. The concrete influences on the end-to-end process are presented in a matrix (Table 2). The matrix representation offers the benefit of linking the induced transformations of the sub-processes with the causative process characteristics and the underlying AI application types. The numbers in the matrix represent the sub-processes in chronological order. For better readability, sub-processes that merge are indicated with the same letter. The process transformations induced by the three AI application types cause 10 mergers, six eliminations, three shifts and nine accelerations of and within the investment advisory sub-processes. Most process mergers occur in the initiation, profiling, concept and offer phases, which are characterized by intense client-advisor interaction.

Transformative process change analysis

Sub-processes like *(1) initial customer contact*, *(3) clarification with compliance* and *(4) analysis of last customer contact* may be integrated since client conversations and segmentations can be analyzed in-time and updated based on the customer profile saved. Also, the sub-processes *(2) identification of customer needs* and *(8) goal formulation* merge since both can be derived with an intelligent CA. Sub-processes *(9) determination of restrictions* and *(11) creation of risk profile* are integrated applying a CA combined with PA for risk analysis. Finally, sub-processes *(13)*, *(14)*, *(16)* merge because the investment simulation and proposal generation are conducted by applying PA. While sub-process eliminations and shifts are observed through the whole process, accelerations take mostly place in the second part of the process where highly standardized and administrative tasks such as *(20) settlement of contract* and *(24) customer reporting* are located, which profit from digital interactions, digital data storage and the transmission of information and insights between the three AI-based application types.

The changes are mostly initiated by CA (18) and CS (14), while PA only causes eight process transformations. An analysis of frequency distributions of process-relevant RA characteristics and induced transformation per AI application type reveal further insights into the impact of RA onto the investment advisory process (Figure 4). First, most sub-process mergers are based on the intelligent CA and CS. This is because such systems are frontend systems affecting the activities and its sequences between the bank advisor and the clients. Second, eliminations are relatively evenly distributed with CS in the lead. This makes sense because customer needs are matched with the risk profile by the CS application type which used to be extensive work for the advisor. On that basis, the application seamlessly identifies cross- and up-selling potential, creates an investment profile, and prepares a solution. Process accelerations are mostly driven by the CA since it enables fast communication between clients and the bank. The majority of investment advisory process changes are caused by efficiency (15), automation (9) and (8) standardization that CA

Table 2. Summary matrix of induced transformations on the sub-process level

Process step	Subprocesses/ activities	Induced transformation				Addressed process-relevant robo-advisory characteristics							AI application type		
		Merger	Elimination	Shift	Acceleration	Accessibility	Automation	Availability	Efficiency	Standardization	Transparency	Usability	Conversational agent	Customer segmentation	Predictive analytics
Initiation	1	a				x	x	x	x			x	x	x	
	2	b							x				x		
	3	a					x		x				x	x	
	4	a					x		x				x		
	CM1			x		x	x	x	x				x		
Profiling	5				x				x	x				x	
	6		x							x				x	
	7				x					x		x	x	x	x
	8	b							x	x		x	x		
	9	c					x			x			x	x	
	10						x								
Concept	11	c								x		x		x	x
	12		x							x				x	
	13	d							x		x	x	x		x
	14	d							x					x	x
	15			x			x			x					
	CM2		x				x		x				x		
Offer	16	d							x				x	x	x
	17		x						x	x		x	x		
	CMn		x				x		x				x		
	18		x							x				x	x
	19				x		x	x	x				x		
	20				x					x			x		
	21			x	x		x		x	x			x		
Implemen tation	22				x		x		x			x	x		
	23														
	24				x	x	x	x	x			x	x		
Maintenance	25				x		x	x	x	x		x		x	x
	26				x				x	x		x		x	x
	Total	*10*	*6*	*3*	*9*	*3*	*14*	*5*	*19*	*14*	*1*	*10*	*18*	*13*	*8*

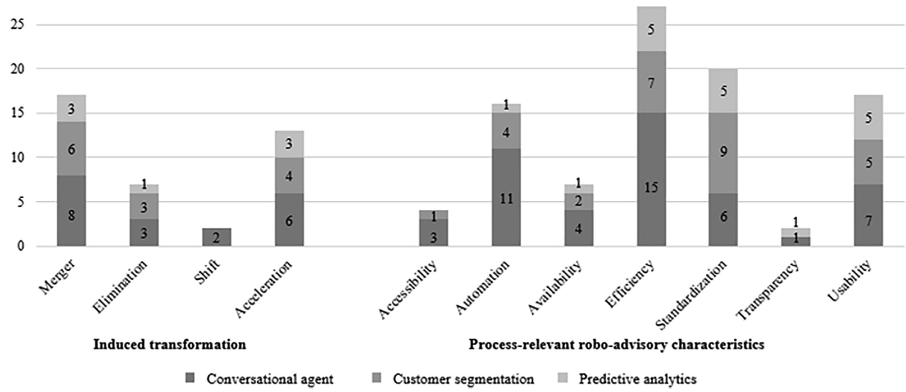

Figure 4.
Frequency distribution of transformations and addressed characteristics

offers. Besides of that, the standardization (10) and efficiency (8) of the intelligent CS account mostly for sub-process mergers and eliminations, while PA brings efficiency (6), standardization (4) and usability (4) into the process. In addition, usability is generated by all three AI application types for both clients and advisors. In contrast to the beforementioned RA characteristics, accessibility (2), availability (4) and transparency (1) only cause a minority of the overall process impact. The reasons lay in the fact that accessibility and availability can only emerge at mandatory contact points. Transparency in the investment advisory process is still provided by the advisor as studies imply (Rühr, 2020) and can only be supplemented by AI-based application systems in *(13) simulation of the best solution*.

Investment advisory process redesign

The impact analysis results of the three AI-based applications CA, CS and PA imply a process redesign with changes in both the sub-process sequence and the system support. In contrast to the traditional PB investment advisory process, the first customer meeting can be conducted either by a CA or bank advisor. Sub-processes (1), (3) and (4) merge due to automation and efficiency gains from the use of intelligent CS and the communication via CA. An analysis of existing customer data along with a set of noncompliant examples allows to automatically estimate risks and flag fraudulent cases. The self-learning systems are continuously improved through iterative feedback to evaluate unknown cases. AI-based chatbots and voice assistants learn and memorize (2) individual client needs to support (8) goal formulation. As part of the client profiling, CA-collected data is used to assign a client segment and for (5) positioning in the right phase of life. With this, the combination of intelligent CS and CA allows (7) to identify and actively offer suitable cross-/upselling options. Further, the CA asks clients questions about risk tolerance and portfolio restrictions in the combined sub-processes (9) and (11). The recorded information is then interpreted by CS and possible market scenarios are contextualized for an accurate risk analysis. The final consolidated client profile (10) is subsequently used to offer the client an investment solution. Compared to the traditional advisory process, the sub-processes (13), (14) and (16) occur simultaneously due to efficiency gains. Here, PA is used for financial asset selection and allocation. Considering the predicted returns, risks and the client's risk tolerance, self-learning algorithms select the best fitting investments. Further suggestions for improvement made by the customer can be discussed interactively in the subprocess (19) customer approval for the overall solution using intelligent CAs. Once the investor is satisfied with the investment solution, a standardized contract can be drafted. With the conclusion of the contract (20), the consultation ends. Analogous to the traditional PB investment advisory, the following implementation of the agreed contract, i.e. (22), (23) and (24), runs without further customer interaction. In the last process step, maintenance, the forecasting capability of PA can be used for the successive assessment of the compatibility of the solution and market development (25). As proposed by Almahdi and Yang (2017), portfolio profitability is continuously checked, and alternative investment instruments are recommended to either the bank advisor or the client (Figure 5).

Evaluation

Four semi-structured, one-hour expert interviews were conducted and transcribed to critically assess the results by applying an interview guideline, which participants received in advance. The questions focus on the applicability of the three application types in the identified process steps and their impact on the process and beyond. All interviewees work in the financial industry and have an association with AI and PB. Expert 1 works as head of innovation management at a German bank, expert 2 is the head of digitization at a Swiss private bank, expert 3 is the head of business technology with a focus on AI and expert 4 is the managing director at a Swiss AI-based asset management FinTech company. The interview results largely confirm the process redesign, but also reveal surprising findings. Regarding CA integration, experts 1, 3 and 4 saw potentials in customer data collection: "It's not just about 'recording' customer data, rather CAs enable a kind of intuitive interaction with the customer". CA usage also depends on product complexity – the more complex the product, the more likely a bank advisor is to add value. Expert 2 views CA-based client onboarding rather critical: ". . . the first client contact in PB must be personal and cannot be established via a conversational system". Still, mobile device-implemented chatbots and voice assistants contribute to the investor's independence of location and time-consuming phone calls or email queues (experts 1, 2 and 4). Yet, efficiency gains of CA depend on domain knowledge and speech flow, since immature assistants decrease client trust (expert 3 and 4). In addition, CAs in PB must follow HNWI regulations, which offers additional potential for advisor support in the consultation documentation (expert 2). Besides that, all experts confirm the applicability of CS in customer acquisition but find external client data availability and processing due to data protection regulations a barrier (expert 3). Moreover, product recommendations based on CS promote service individualization and risk-adequate investments while improving the client journey (expert 2 and 4). While expert 1 recognizes potential for CS-based, dynamic client segmentation, expert 2 takes a rather critical view of this approach: "The compliance department may be interested in different segmentations than those who create the offers". Regarding PA integration, experts 1, 3 and 4 mention that analyzing alternative and unstructured data helps to identify lucrative investment solutions. Expert 4 thereby emphasizes the potential of standardizing processes internally which would enable banks to process client information across channels and systems and hence individualize services and products toward the clients. Nevertheless, the interviewees fear that efficiency gains tend to favor banks rather than customers. AI-based automation may diminish client trust since "trust is not scalable" (expert 4). Also, internal bank tensions may arise as human advisors find themselves in competition with intelligent applications and are overwhelmed by the AI-based automation (expert 2 and 3). Expert 2 even warns against automating organizations too quickly. In the case of a Swiss private bank, automation led to the loss of employees because they felt overstrained by the rapid digitalization.

Discussion

Implications for AI-assisted private banking investment advisory

Based on the impact analysis and expert interviews, three implication dimensions for PB investment advisory are derived. *First*, AI-based automation is driven by the AI application

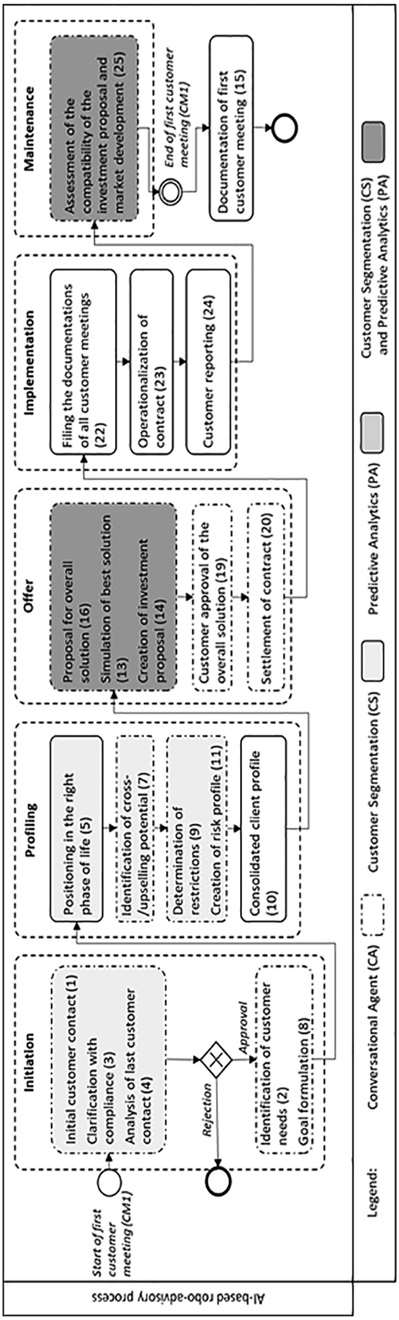

Figure 5.
The re-designed AI-based private banking investment-advisory process

types CA and CS which standardize the process and hence enable advisory flexibility. On the one hand, CAs help advisors to stay informed about the clients by identifying needs and reporting them. This increases consulting service efficiency, as the bank advisor can discuss uncommunicated needs with clients and proactively present solutions. On the other hand, CS and partly PA drive process automation and relieve advisors of analytical tasks, enabling an intense relationship management across the different channels as well as regular market and product insights. All relevant AI-based market and product insights should be communicated regularly or even ad hoc to the clients online or offline. Hence, advisory can focus on their banking professional role, while the AI application types increasingly take over the analytical role. *Second*, AI-based process automation requires strategic integration of the three AI-based application types in the form of an omnichannel approach, which mainly evolves around CA. The degree of accessibility and availability that CA brings into the process for both clients and advisors allows connecting with different online and offline channels. Nevertheless, advisors only remain the client focus if they are reachable through different direct and indirect channels since the application type also provides clients with intelligent self-services such as analyses and interpretations which are created by CS and PA systems. Hence, client journeys need to be formalized to seamlessly integrate AI-driven insights for both clients and advisors. Direct channels such as branch, telephone, email and video conferencing are time-intensive from the advisors' viewpoint but remain important to establish personal client relationships. Above all, it is important to ensure that there are no media discontinuities between the direct and indirect channels (e.g. online banking and bank-specific apps), to maximize customer flexibility and experience. *Third*, an omnichannel approach that integrates the three AI application types into a consulting-intensive process requires structured human-AI interaction. The combined use of all three applications can contribute to improving efficiency, transparency and usability, provided that the collaboration between humans and machines is purposeful and thus sustainable. While advisors remain the face to the clients especially when it comes to complex products, they increasingly generate value through collaboration with AI-based applications. For encouraging clients to use intelligent services, system design should place emphasis on usability to gain client trust. Furthermore, sequential decision-making between advisors and AI systems is proposed with the advisor having a veto right, which is required by regulation to ensure transparency. If banks offer their customers intelligent self-services, the definition of human–machine interaction at the customer–bank interface is also necessary to provide seamless client journeys, avoid communication breaks between solutions, advisors and clients, as well as to build trust regarding AI use. The multiple channels require the advisor to act as an internal and external network coordinator and deliver hybrid, AI-assisted services. *All in all*, CA has the overall highest impact on PB investment advisory since the process is communication-intensive by nature and the NLP capabilities of CA are well-suited to support PB advisors. The effects of the CS and PA application types, in turn, unfold in an indirect way, since these, especially CS, are for internal bank use and, unlike CA, are not representing a direct customer interface. CS and PA, nonetheless, are the underlying analytical components of the CA application type that ultimately lead to added customer value. Hence, AI-assisted PB investment advisors are asked to (1) perform professional banking tasks such as risk profile creation, (2) interpret AI-based analyses and interpretations to create valuable insights, (3) coordinate between AI-based systems and interpersonal client actions and finally (4) integrate knowledge into these systems. In addition, customer needs may be related to non-banking services and must be coordinated with other service providers. Due to the AI integration into the PB investment advisory process, the advisor task range increases and raises the question whether the advisor role should be split into one role covering banking professional tasks toward the client and a second role being responsible for data analysis and interpretation (see Figure 6).

Limitations and future research

As the first limitation, the process impact analysis, redesign and implications presented are tailored for PB and are not generally applicable to retail banking. Nevertheless, the results can be used for the design of AI-based service processes. Second, the process impact analysis and re-design is based on a reference process which can vary in other financial institutions. Hence, the present study is not replacing a detailed analysis of individual processes. Third, the three AI application types are abstract, generic descriptions of varying degrees of complexity, which only allow for implications at the conceptual level. For the redesign of company-specific processes, the concrete applications and their respective process-related effects must be analyzed. While the process re-design indicates usage of the AI application types CA, CS and PA in PB investment advisory, the paper is not providing concrete human-AI interactions along the sub-processes. The work of Dellermann *et al.* (2019a) on human-AI collaboration can be used as a foundation. Further research could also examine the proposed sequential decision-making design between AI systems and advisors and investigate effects on the system adoption from both the client and advisor perspective, e.g. based on the research of Shrestha, Ben-Menahem, and von Krogh (2019). Additionally, client trust towards AI usage within the process should be analyzed. Since AI-based systems affect the available channels, customer experience should be investigated and appropriate multichannel solutions designed. Besides that, further research could focus on required PB advisory skills in the newly designed process. Moreover, AI system design research must consider that the human advisor may suffer from both a high degree of automation and information overload within the AI-based process. The latter has already been indicted by the research results of Dietzmann and Duan (2022). Future research could therefore address how to increase employee well-being in AI-based workflows so that employees achieve long-term success in collaboration with the algorithms. Approaches for such research include the work of Kellogg, Valentine and Christin (2020), which describes the "6 Rs" (recommending, restricting, recording, rating, replacing, and rewarding) of algorithmic control of employers, which in turn elicit six corresponding positive and negative experiences among employees.

Conclusion

This article presents an AI process impact analysis of RA-based AI application types on the PB investment advisory process developed by Nueesch *et al.* (2016). The impact analysis was performed by examining three AI-based RA application types and the associated seven process-relevant RA characteristics for their transformation potential in the sub-processes, which can manifest itself in a merger, elimination, shifting, or acceleration of the respective sub-processes. The impact analysis results imply that efficiency, standardization, usability, and automation gains induced by the AI application types trigger process changes. Additionally, the expert interviews largely confirmed the proposed process redesign and three organizational implications of AI for PB are derived. First, AI-based and automated systems support client

	Dimension	Crucial AI application type	Supportive RA characteristics	Implications	Client benefits
1	*AI-based automation*	*CA* and *CS*	*Automation* and *standardization*	• Enables advisory flexibility in favor of client interaction and need identification • Split banking professional and analytical role	• Personal advisor relation through different channels • Regular market and product insights
2	*Omnichannel approach*	*CA*	*Accessibility* and *availability*	• Client journey across direct and indirect channels • Avoid media breaks to ensure client flexibility • Support with AI-based analyses and interpretations	• Broad choice of channels and channel-independent bank contact • Intelligent self-servicing
3	*Human-AI interaction*	*CA*, *CS* and *PA*	*Efficiency, transparency* and *usability*	• Advisor is face to the client, network coordination • AI usage depends on product complexity, system usability and client trust in AI • AI-assisted decision-making with advisor veto right	• Highly individual product and service proposals • Holistic coverage of needs

Figure 6.
Implications and client benefits on AI-assisted private banking investment advisory

advisors in analytical tasks and enable them to act more flexible toward the client through different direct and indirect channels. Hence, the bank advisor role may be divided into one banking-professional and one analytical role with the latter role eventually being covered by an AI system. Second, AI-based process automation and the provision of intelligent self-services require an omnichannel approach. This aspect is crucial to enable individual client journeys and create value by providing both bank advisors and clients with AI-based analyses and interpretations. Third, AI-based automation and the integration of an omnichannel approach demand active design of task-specific human–AI interaction toward bank advisors and clients. Overall, the advisor should remain the face to the client and orchestrate identified client needs also beyond banking products and services. Clients are expected to use AI systems depending on product complexity, system usability and trust in the solution. To avoid a decrease of client trust through AI implementation, a sequential decision-making structure from AI to human should be integrated and customer advisors as well as clients should thus be assigned a veto right for the AI applications. If private banks consider the identified implications, the use of AI in PB investment advisory can generate added value in the form of personalized advice and individualized product and service offerings. It should be noted that the PB advisor will have an even more comprehensive role, as a better understanding of customer needs beyond financial aspects will emerge because of AI systems. Hence, the AI-driven disruptions will further open the banking industry and require advisors to increasingly operate as coordinators in the internal and external network to generate client value.

From a scientific perspective, the present study contributes to the business process redesign research stream by providing (1) AI application and application-related process characteristics on the example of RA, (2) an impact analysis approach to assess AI-based business process redesign and (3) guidance for AI-driven organizational design on the example of industry-specific implications. Furthermore, the analysis of the four sub-process transformations merger, elimination, shifting and acceleration implies that AI-driven process redesign is mostly induced by interaction-intense sub-processes affected by CA. By applying AI application characteristics and the four mentioned process transformations, the impact analysis approach extends knowledge on the technology-induced business process redesign (Mansar & Reijers, 2007). The generated knowledge may serve research and practice as a fundament for investigations on AI deployment in advisory processes. Moreover, practitioners receive a blueprint for a structured AI impact analyses for process redesign that is based on three AI application types and exemplary application-related process characteristics that allow companies to derive organizational implications along the causal chain of the impact analysis. Additionally, the results of the present study provide PB practitioners with concrete suggestions for the future of PB investment advisory, where advisors interact and decide together with AI-based systems.

References

Accenture. (2018). Private banking in your pocket. Available from: https://www.accenture.com/_acnmedia/pdf-79/accenture-pov-digital-wealth-management-private-banking-in-your-pocket.pdf

Adam, M., Toutaoui, J., Pfeuffer, N., & Hinz, O. (2019). Investment decisions with robo-advisors: The role of anthropomorphism and personalized anchors in recommendations. In *ECIS 2019 Proceedings*. Available from: https://aisel.aisnet.org/ecis2019_rp/33

Almahdi, S., & Yang, S. Y. (2017). An adaptive portfolio trading system: A risk-return portfolio optimization using recurrent reinforcement learning with expected maximum drawdown. *Expert Systems with Applications*, *87*, 267–279, doi: 10.1016/j.eswa.2017.06.023.

Alt, R., & Puschmann, T. (2012). The rise of customer-oriented banking—electronic markets are paving the way for change in the financial industry. *Electronic Markets*, *22*(4), 203–215, doi: 10.1007/s12525-012-0106-2.

Alt, R., Beck, R., & Smits, M. T. (2018). FinTech and the transformation of the financial industry. *Electronic Markets*, *28*(3), 235–243, doi: 10.1007/s12525-018-0310-9.

Althelaya, K. A., El-Alfy, E.-S. M., & Mohammed, S. (2018). Evaluation of bidirectional LSTM for short- and long-term stock market prediction. In *2018 9th International Conference on Information and Communication Systems (ICICS)* (pp. 151–156). doi: 10.1109/IACS.2018.8355458.

Becchi, S. M., Hamaloglu, U., Aggarwal, T. and Panchal, S. (2018), *The evolution of Robo-advisors and Advisor 2.0 model: The future of investment management and financial advisory*, Ernst & Young Global Limited.

Beck, A. D. (2020). The role of artificial intelligence in robo-advisory. In *Robo-Advisory* (pp. 227–243). Palgrave Macmillan.

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

Boobier, T. (2020). Machine learning, AI and 'apps'. In *AI and the Future of Banking* (pp. 93–113). Wiley.

Brodski, S. (2019). What does Personalization in banking really mean? *BCG*. Available from: https://www.bcg.com/publications/2019/what-does-personalization-banking-really-mean

Bruckes, M., Westmattelmann, D., Oldeweme, A., & Schewe, G. (2019). Determinants and barriers of adopting robo-advisory services. In *ICIS 2019 Proceedings* (Vol. 10).

Burnett, R. (2017). The most helpful 'banking assistant' on Facebook. *Wells Fargo*. Available from: https://stories.wf.com/helpful-banking-assistanton-facebook/

Climescu, A. M., von Keitz, C., Rocholl, J. and Sander, M. (2021), "How can Robo-advisory be implemented and integrated into existing banks?", *Robo-Advisory*, Palgrave Macmillan, Cham, pp. 187-223.

Cocca, T. (2016). Potential and limitations of virtual advice in wealth management. *Journal of Financial Transformation*, *44*, 45–57.

Coombs, C., & Redman, A. (2018). The impact of robo-advice on financial advisers: A qualitative case study. In *UK Academy for Information Systems Conference Proceedings 2018*.

Crosman, P. (2018), "How artificial intelligence is reshaping jobs in banking", *American Banker*, Vol. 183 No. 88, p. 1.

D'Acunto, F., Prabhala, N. and Rossi, A. G. (2019), "The promises and pitfalls of robo-advising", *The Review of Financial Studies*, Vol. 32 No. 5, pp. 1983-2020.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, *96*(1), 108–116.

Day, M.-Y., & Lin, J.-T. (2019). Artificial intelligence for ETF market prediction and portfolio optimization. In *Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining* (pp. 1026–1033). doi: 10.1145/3341161.3344822.

Day, M. Y., Lin, J. T. and Chen, Y. C. (2018), "Artificial intelligence for conversational robo-advisor", *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, pp. 1057-1064.

Dellermann, D., Calma, A., Lipusch, N., Weber, T., Weigel, S., & Ebel, P. (2019a). The future of human-AI collaboration: A taxonomy of design knowledge for hybrid intelligence systems. In *HICSS Proceedings* (pp. 274–283).

Dietzmann, C., & Alt, R. (2019). How IT-related financial innovation influences bank risk-taking: Results from an empirical analysis of patent applications. In *2019 IEEE 21st Conference on Business Informatics (CBI)* (Vol. 1, pp. 452–461). doi: 10.1109/CBI.2019.00059.

Dietzmann, C., & Duan, Y. (2022). Artificial intelligence for managerial information processing and decision-making in the era of information overload. In *Hawaii International Conference on System Sciences*. doi: 10.24251/HICSS.2022.720.

Dietzmann, C., Heines, R., & Alt, R. (2020). The convergence of distributed ledger technology and artificial intelligence: An end-to-end reference lending process for financial services. In *Proceedings: Twenty-Eighth European Conference on Information Systems (ECIS2020)* (Vol. 18).

Eickhoff, M., Muntermann, J., & Weinrich, T. (2017). What do FinTechs actually do? A taxonomy of FinTech business models. In *ICIS 2017 Proceedings* (Vol. 22).

Fein, M. L. (2015). Robo-advisors: A closer look. [working paper]. Fein Law Offices.

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

Forbes Insights. (2019). The next-generation wealth manager.

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

Gold, N. A. and Kursh, S. R. (2017), “Counterrevolutionaries in the financial services industry: teaching disruption – a case study of roboadvisors and incumbent responses”, *Business Education Innovation Journal*, Vol. 9 No. 1, pp. 139-146.

Gu, C. -S., Hsieh, H.-P., Wu, C. -S., Chang, R.-I., & Ho, J.-M. (2019). A fund selection robo-advisor with deep-learning driven market prediction. In *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)* (pp. 2845–2850). doi: 10.1109/SMC.2019.8914183.

Guo, F., Cheng, X., & Zhang, Y. (2019). A conceptual model of trust influencing factors in robo-advisor products: A qualitative study. In *WHICEB 2019 Proceedings*. Available from: https://aisel.aisnet.org/whiceb2019/48

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, *28*(1), 75–105. doi: 10.2307/25148625.

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. doi: 10.1007/s11747-020-00753-z.

Hoelscher, R., & Nelde, M. (2018). Darstellung, Funktion und Portfolioaufteilung von Robo-Advisory. *Zeitschrift Für Das Gesamte Kreditwesen*, *2*, 68–73.

Joshi, A., Lavanchy, M., & Stehli, S. (2018). *Data Analytics & artificial intelligence: What it means for your business and society*. IMD.

Jung, D., & Weinhardt, C. (2018). Robo-advisors and financial decision inertia: How choice architecture helps to reduce inertia in financial planning tools. In *ICIS 2018 Proceedings*. Available from: https://aisel.aisnet.org/icis2018/hcri/Presentations/4

Jung, D., Dorner, V., Glaser, F., & Morana, S. (2018a). Robo-Advisory: Digitalization and automation of financial advisory. *Business and Information Systems Engineering*, *60*(1), 81–86. doi: 10.1007/s12599-018-0521-9.

Jung, D., Dorner, V., Weinhardt, C., & Pusmaz, H. (2018b). Designing a robo-advisor for risk-averse, low-budget consumers. *Electronic Markets*, *28*(3), 367–380. doi: 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: Recent Findings and Practical Cases* (pp. 405–427). Springer International Publishing. doi: 10.1007/978-3-319-95999-3_20.

Kaya, O., Schildbach, J. and Schneider, S. (2017), “Robo-advice – a true innovation in asset management”, *Deutsche Bank Research*, pp. 1-16.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, *14*(1), 366–410. doi: 10.5465/annals.2018.0174.

Khadivizand, S., Beheshti, A., Sobhanmanesh, F., Sheng, Q. Z., Istanbouli, E., Wood, S., & Pezaro, D. (2020). Towards intelligent feature engineering for risk-based customer segmentation in banking. In *Proceedings of the 18th International Conference on Advances in Mobile Computing and Multimedia* (pp. 74–83). doi: 10.1145/3428690.3429172.

Kilic, M., Dolata, M., & Schwabe, G. (2017). Why do you ask all those questions? Supporting client profiling in financial service encounters. In *Hawaii International Conference on System Sciences*. doi: 10.24251/HICSS.2017.572.

Kilic, M., Heinrich, P., & Schwabe, G. (2015). Coercing into completeness in financial advisory service encounters. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work and Social Computing* (pp. 1324–1335). doi: 10.1145/2675133.2675289.

Kinniry, F. M., & DiJoseph, M. A. (2014). *Putting a value on your value: Quantifying vanguard adviser's alpha in the UK*. Vanguard.

Kothari, K., & Berry, T. (2021). Wealth management top trends 2021. Capgemini. Available from: https://worldwealthreport.com/wp-content/uploads/sites/7/2020/12/Top-Trends-2021-in-Wealth-Management.pdf

Law, K. S., & Chung, F.-L. (2020). Knowledge-driven decision analytics for commercial banking. *Journal of Management Analytics*, *7*(2), 209–230. doi: 10.1080/23270012.2020.1734879.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553). 436–444, doi: 10.1038/nature14539.

Li, R., Kahou, S., Schulz, H., Michalski, V., Charlin, L., & Pal, C. (2019). Towards deep conversational recommendations. (ArXiv).

Liao, L., Ma, Y., He, X., Hong, R., & Chua, T.-S. (2018). Knowledge-aware multimodal dialogue systems. In *Proceedings of the 26th ACM International Conference on Multimedia* (pp. 801–809). doi: 10.1145/3240508.3240605.

Mansar, L. S., & Reijers, H. A. (2007). Best practices in business process redesign: Use and impact. *Business Process Management Journal*, *13*(2), 193–213. doi: 10.1108/14637150710740455.

McDonald, J. (2019). *Identifying and streamlining low risk customers or applicants: Techniques and benefits*. The Fraud Practice.

Mesbah, N., Tauchert, C., Olt, C., & Buxmann, P. (2019). Promoting trust in AI-based expert systems. In *AMCIS 2019 Proceedings*. Available from: https://aisel.aisnet.org/amcis2019/ai_semantic_for_intelligent_info_systems/ai_semantic_for_intelligent_info_systems/6

Morana, S., Gnewuch, U., Jung, D., & Granig, C. (2020). The effect of anthropomorphism on investment decision-making with robo-advisor chatbots. In *ECIS 2020 Proceedings*.

Moulliet, D., Majonek, A., Stolzenbach, J., & Völker, T. (2016a). *The expansion of robo-advisory in wealth management*. Deloitte.

Moulliet, D., Stolzenbach, A., Bein, A., & Wagner, I. (2016b). *Cost-income ratios and robo-advisory: Why wealth managers need to engage with robo-advisors*. Deloitte.

Nüesch, R., Alt, R., & Puschmann, T. (2015). Hybrid customer interaction. *Business and Information Systems Engineering*, *57*(1), 73–78, doi: 10.1007/s12599-014-0366-9.

Netjes, M., Mansar, S. L., Reijers, H. A. and van der Aalst, W. M. (2007), "Performing business process redesign with best practices: An evolutionary approach", *International Conference on Enterprise Information Systems*, Springer, Berlin, Heidelberg, pp. 199-211.

Nueesch, R., Puschmann, T., & Alt, R. (2014). Realizing value from tablet-supported customer advisory: Cases from the banking industry. In *BLED 2014 Proceedings*.

Nueesch, R., Zerndt, T., Alt, R., & Ferretti, R. G. (2016). Tablets penetrate the customer advisory process: A case from a Swiss private bank. In *BLED 2016 Proceedings* (Vol. 18).

O'Keefe, D., Warmund, J., & Lewis, B. (2016). Robo advising–Catching up and getting ahead. Available from: https://assets.kpmg/content/dam/kpmg/pdf/2016/07/Robo-Advising-Catching-Up-And-Getting-Ahead.pdf

Oliveira, N., Cortez, P., & Areal, N. (2017). The impact of microblogging data for stock market prediction: Using Twitter to predict returns, volatility, trading volume and survey sentiment indices. *Expert Systems with Applications*, *73*, 125–144. doi: 10.1016/j.eswa.2016.12.036.

Ostern, N., Schöler, J., & Moormann, J. (2020). Toward voice-enabled robotic advisory for personalized wealth management. In *AMCIS 2020 Proceedings*. Available from: https://aisel.aisnet.org/amcis2020/ai_semantic_for_intelligent_info_systems/ai_semantic_for_intelligent_info_systems/1

Panebianco, M., & Folcia, M. (2016). Robo Advisory moves forward in Italy. Available from: https://www.pwc.com/it/it/publications/assets/docs/robo-advisory-italy.pdf

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, *24*(3), 45–77, doi: 10.2753/MIS0742-1222240302.

Perrin, S., & Roncalli, T. (2020). Machine learning optimization algorithms and portfolio allocation—machine learning for asset management—wiley online library. *ArXiv*, 261–328.

Poterba, J. M., & Shoven, J. B. (2002). Exchange-traded funds: A new investment option for taxable investors. *AER*, *92*(2), 422–427.

Renaux, M., Rudnicki, M., Beniere, A., & Lorain, F. (2019). How will robo-advisory reshape asset management? *Initio*.

Ruf, C., Back, A., Bergmann, R., & Schlegel, M. (2015). *Elicitation of requirements for the design of mobile financial advisory services - instantiation and validation of the requirement data model with a multi-method approach*. In *2015 48th Hawaii International Conference on System Sciences* (pp. 1169-1178). IEEE.

Rühr, A. (2020). Robo-advisor configuration: An investigation of user preferences and the performance-control dilemma. In *ECIS 2020 Proceedings*.

Rühr, A., Berger, B., & Hess, T. (2019). Can I control my robo-advisor? Trade-offs in automation and user control in (digital) investment management. In *AMCIS 2019 Proceedings*.

Russell, S. J. and Norvig, P. (2016), *Artificial intelligence: A modern approach*, Pearson Education, Malaysia.

Sachse, S., Puschmann, T., & Alt, R. (2012). Towards customer-oriented electronic markets – a survey among digital natives in the financial industry. In *Bled 2012 Proceedings* (Vol. 22).

Schabicki, T., Quint, Y., & Schroeder, S. (2020). (Re-) launching a robo-advisor as a bank. In *Robo-Advisory* (pp. 163–185). Palgrave Macmillan.

Schindler, J., de Souza Moraes, A., Li, S.-P., Bruno, G., Marcucci, J., Moscatelli, M., . . . Mueller, H. (2017). *Artificial intelligence and machine learning in financial services: Market developments and financial stability implications*. Financial Stability Board.

Shrestha, Y.R., Ben-Menahem, S.M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, *61*(4), 66–83.

Singh, I. and Kaur, N. (2017), "Wealth management through robo advisory", *International Journal of Research-Granthaalayah*, Vol. 5 No. 6, pp. 33-43.

Sironi, P. (2016), *FinTech innovation: From robo-advisors to goal based investing and gamification*, Wiley, Hoboken, New Jersey.

Statista. (2021a). Robo-advisors—deutschland. Available from: https://de.statista.com/outlook/dmo/fintech/personal-finance/robo-advisors/deutschland

Statista. (2021b). Robo-advisor—worldwide. Available from: https://www.statista.com/outlook/337/100/robo-advisors/worldwide

Tauchert, C. and Mesbah, N. (2019), "Following the robot? Investigating users' utilization of advice from Robo-advisors", *ICIS*.

Tertilt, M., & Scholz, P. (2018). To advise, or not to advise. *The Journal of Wealth Management*, *21*(2), 70–84.

Tsiptsis, K. K. and Chorianopoulos, A. (2011), *Data mining techniques in CRM: inside customer segmentation*, John Wiley & Sons, Hoboken, New Jersey.

von Martens, O. O. T., & Schildbach, J. (2019). *German robo-advisors*. Deutsche Bank Research.

Wang, S. (2020). Problems with older adults' adoption of robo advisors: An empirical study. In*AMCIS 2020 TREOs*. Available from: https://aisel.aisnet.org/treos_amcis2020/8

Wang, P. -Y., Liu, C. -S., Yang, Y. -C., & Huang, S. -H. (2019). A robo-advisor design using multiobjective RankNets with gated neural network structure. In *2019 IEEE International Conference on Agents (ICA)*, 77–78. doi: 10.1109/AGENTS.2019.8929188.

Webersinke, H. (2017). *Dritte Befragung des Instituts für Vermögensverwaltung*. TH Aschaffenburg.

Webster, J. and Watson, R. T. (2002), "Analyzing the past to prepare for the future: Writing a literature review", *MIS Quarterly*, Vol. 26 No. 2, pp. 8-24.

Winter, R. (2008). Design science research in Europe. *European Journal of Information Systems*, *17*(5), 470–475. doi: 10.1057/ejis.2008.44.

Woodyard, A. S., & Grable, J. E. (2018). Insights into the users of robo-advisory firms. *Journal of Financial Service Professionals*, *72*(5), 56–66.

Xue, J., Zhu, E., Liu, Q., & Yin, J. (2018). Group recommendation based on financial social network for robo-advisor. *IEEE Access*, *6*, 54527–54535. doi: 10.1109/ACCESS.2018.2871131.

Yan, R. (2018). 'Chitty-Chitty-Chat bot': Deep learning for conversational AI. In *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence* (pp. 5520–5526). doi: 10.24963/ijcai.2018/778.

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