Robo-Advisors: A Big Data Challenge

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This is a pre-print of the chapter:

Severino, F., Thierry, S. (2022). *Robo-Advisors: A Big Data Challenge*. In: Walker, T., Davis, F., Schwartz, T. (eds) *Big Data in Finance*. Palgrave Macmillan.

https://doi.org/10.1007/978-3-031-12240-8_7

Abstract

At the frontier of personal finance and Fintech, robo-advisors aim to provide customized portfolio strategies without human intervention. They typically propose passive strategies that can match the investor's objectives and risk profile at a low cost. However, digital advisors feature a lack of precision in capturing clients' attitude towards risk and a (not always suitable) low risk exposure. In this context, leveraging big data and artificial intelligence techniques can improve the main strength of robo-advisors, that is, their ability to automatically provide personalized investment solutions. Text data from dialogue systems, such as chatbots, can be employed to improve the client's profiling, while recommendation systems can rely on big data from financial social networks to propose targeted investment strategies. Analysis of big data through machine learning methods can also improve the performance of the optimization algorithms employed by digital advisors. The potential for the exploitation of big data and artificial intelligence in automated asset management is still enormous.

Keywords: robo-advisors, Fintech, portfolio management, big data, artificial intelligence.

1.0 Introduction

The 2008 global financial crisis led to the belief that the growing development of digital technologies would gradually make traditional financial institutions disappear in favor of Fintech firms (Stulz, 2019). It is in this context of digital transformation that robo-advisors entered the market. In fact, these instruments are part of an already long-standing modernization trend in the financial industry. Phoon and Koh (2018) claim that the last half-century saw the increasing development of innovative technologies concerning security trading, transaction processing, and advisory services to investors. Digital advisors remarkably contribute to these areas. Specifically, these are defined by the Sovereign Wealth Fund Institute (2015) as "a type of financial advisor that provides web-based portfolio management with almost zero human intervention. These online advisors typically use algorithms and formulas to conduct portfolio management".

Appearing more frequently after the global financial crisis in 2008, the first robo-advisors essentially focused on passive portfolio strategies via ETFs and exploited algorithms to automatically rebalance positions. This approach, which reflected investors' prudent attitude at the time, led to the increased development of robo-advisors for passive asset management (Phoon and Koh, 2018).

As robo-advisors become increasingly important in the financial industry, several aspects of this novel technology should be investigated. On the one hand, many authors highlight the advantages offered by robo-advisors. For instance, Uhl and Rohner (2018) argue that many human managers do not sufficiently take into account the investment personality of individuals. It is essential that the proposed asset allocation matches the investor's attitude towards risk, especially for long-term investors. Robo-advisors could, thus, offer a higher degree of customization to investors.

On the other hand, several studies are rather critical of robo-advisors' simplicity and their lack of sophistication. For example, Tertilt and Scholz (2018) show that the algorithms used to classify clients into different risk profiles often turn out to be too simplistic. They believe robo-advisors are currently in their initial stage of development, but that this technology has the potential to evolve. Furthermore, Fisch, Labouré, and Turner (2019) observe that, given the over-simplified design of robo-advisors, more and more companies choose to combine the characteristics of robo-advisors with those of traditional human managers. Interestingly, the (partially) automated investment process of such "hybrid robots" induces a relevant reduction of fees, while retaining the option for investors to communicate with a human portfolio manager.

Finally, digital advisors present other critical issues, as discussed in the literature. According to a report from the Financial Industry Regulatory Authority (FINRA, 2016), clients of robo-advisors are often left to determine whether the investment strategy proposed by the robot actually meets their needs. Fein (2015) also notes that robo-advisors take little account of the intrinsic characteristics of the client, which could be detrimental in the event of a major financial crisis.

In this chapter, we first illustrate the characteristics of robo-advisors, emphasizing their strengths and weaknesses. Then, we focus on how digitization and the use of big data can impressively improve the performance of automated asset managers. Indeed, big data analytics can boost the customization of the financial strategies offered by digital advisors. The latter could target investors with more and more specific needs and propose extremely tailored investment solutions thanks to the information extracted from social network data or from the client's interaction with a chatbot. At its current stage, the application of such technologies to automated advisory is still embryonic in the financial industry, but its development potential is huge.

2.0 Robo-advisor features, benefits, and drawbacks

Nicoletti (2017) lists robo-advisors among contemporary promising Fintech innovations that are reshaping the industry of financial services (see Chapter 4 therein). In the following subsections, we illustrate the main characteristics of digital advisors by focusing on their advantages and disadvantages with respect to traditional human financial consultants. Table 1, at the end of the following section, summarizes the main points of our discussion.

2.1. Generalities and recent trends in the financial industry

Robo-advisors are becoming increasingly widespread globally, particularly in North America, Europe, and South-East Asia. A list of representative robo-advisory companies is provided in Table 7.1 of Xing, Cambria, and Welsch (2019), while Benson (2022) provides a snapshot of the most popular robo-advisors as of March 2022 in a Nerdwallet article.

Not all robo-advisors are equal, and some offer much more advanced services than others. In a Deloitte (2016) report by Moulliet, Stolzenbach, Majonek, and Völker, robo-advisors are classified into four broad categories. First- and second-generation bots are based solely on the use of an online questionnaire that serves as the basis for determining clients' risk level. The asset allocation is then fully defined and adjusted by a traditional portfolio manager. Third and fourth generation robo-advisors are much more developed as they use quantitative methods and algorithms to build and rebalance portfolios. Unlike first- and second-generation machines, they perform fully automated portfolio management throughout the investment process. Figure 1 illustrates the details of these categories.

Figure 2 of Jung, Dorner, Glaser and Morana (2018) summarizes the process of automated financial consulting by comparing it with the human alternative. The product configuration by robo-advisors replaces the traditional meeting with the client, profiling, and the definition of targets. The construction of a suitable portfolio is then provided in an automated way by robo-advisors which match the client's profile with existing financial products (with a preference for passive investing through ETFs). Finally, the traditional portfolio rebalancing and the feedback to the client is also automatically implemented by digital advisors.

According to Phoon and Koh (2018), robo-advisors can be classified into three broad categories.

1. **Direct-to-consumer (D2C) model:** applies to online platforms that provide automatic portfolio management without human intervention.
2. **Business-to-business (B2B) model:** refers to platforms that help traditional financial advisors to offer a digital wealth management solution.

3. **Hybrid model:** includes personalized services for clients but also offers automated portfolio recommendations.

D2C models are probably the most iconic kind of robo-advisors, an example of these being the personal finance company SoFi. The service is provided by an application which can be easily accessed via a smartphone. Due to product flexibility, the target clientele is extremely diversified in terms of wealth, age, and financial needs.

Concerning the B2B model, Fisch, Labouré, and Turner (2019) document a recent increased use of robo-advisors as a digital tool for human advisors. The automated advisory allows portfolio managers to better guide their customers and design the most appropriate investment strategy. This approach has been followed, for instance, by the Raymond James Financial group.

As for hybrid models, Fisch, Labouré, and Turner (2019) acknowledge an increase in the hybridization of digital advisors in the United States: firms frequently combine the characteristics of digital advisors with those of traditional human managers. Hybrid robo-advisors require lower management fees because of their partially automated investment process. However, such hybrid bots also allow their clients to speak with a human advisor.

Hybrid robo-advisors increase competition between firms and create an appetite for heterogeneous types of clients. For example, the digital advisor Betterment offers three different levels of services. The first-level service is a standard robo-advisor, with no possible contact with a human advisor. The second-level service provides unlimited access to financial experts and licensed professionals. The third-level offer provides access to a dedicated advisor, in addition to automated consulting. The latter is attractive for mature, high-net-worth investors, whereas standard robo-advisor users are generally less wealthy and younger. This view is consistent with the digression of Weisser (2016) on Consumer Reports.

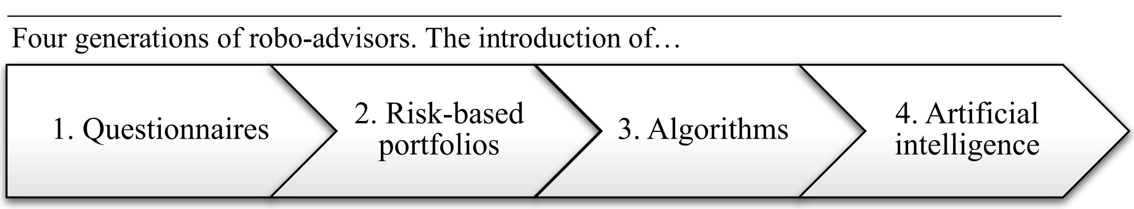

Figure 1. The development of robo-advisors. More details in Deloitte (2016) report by Moulliet, Stolzenbach, Majonek, and Völker.

2.2. Robo-advisor benefits

One of the most remarkable advantages of digital advisors is the personalization (or customization) of the financial product they offer. As discussed in Chapter 1 of Sironi (2016), robo-advisors constitute the main innovative tool in the panorama of personal finance, together with goal-based investing and gamification. The structure of digital advisors allows for the tailoring of financial investments and precisely targets potential clients (such as tech-savvy millennials). Such innovations, that are fostered by big data analytics and fintech digitalization, are still under development and the related technological changes are progressing rapidly (see Section 3). In addition, still in the light of individualization, robo-advisors can be set to optimize after-tax returns and harvest tax loss, which are investor specific. This feature is also addressed by Jung, Glaser, and Köpplin (2019).

Beyond customization, the advantages that robo-advisors offer over humans have been widely studied in the literature. In particular, Uhl and Rohner (2018) show that digital advisors have three main competitive advantages over traditional portfolio managers.

The first advantage concerns the optimal asset allocation proposed by robo-advisors according to the investors' goals and profiles. In order for investments to be successful, it is important to design a robust and well-diversified asset allocation across a broad universe of assets and it is crucial that such allocation perfectly match the investor's objectives and risk profile. Uhl and Rohner (2018) argue that, contrary to robo-advisors, many human portfolio managers do not sufficiently take into account the investment personality of individuals. For instance, during market downturns, a portfolio manager might decide to reduce risk even though the client is not particularly risk averse. This kind of decision can affect the probability of achieving the client's desired investment objectives.

The second comparative advantage of digital advisors is their cost. While traditional institutions mostly offer personalized investment strategies to their wealthier clients, robo-advisors can offer personalized solutions to less affluent clients too, thanks to their less expensive technology platform. As argued by Sharpe (1991) and empirically assessed by Fama and French (2010), on average, active management is a zero-sum game before fees and even a negative-sum game after fees, and the performance of actively managed funds tends to be inconsistent over time. On the contrary, digital advisors rely on passive portfolio strategies, which are automated and, thus, much cheaper. An exact quantification of transaction cost saving in digital advisory is difficult to obtain because of the discretion in the comparable alternative to be considered. For the same investment target, humans and robo-advisors would propose different asset allocations with different ex-post returns. However, since robo-advisors rely on passive investment, comparing the cost-effectiveness of passive versus active asset management can provide an indication of the amount saved. For instance, French (2008) estimates an outperformance of passive investing over the average of all active and passive investors, amounting to 67 basis points for the years 1980-2006. With due simplifications, this corresponds to at least 10% of the expected real return on the U.S. stock market. Moreover, by focusing on robo-advisors, Uhl and Rohner (2018) approximate the total expense ratio (TER) of digital advisors to 0.5%, while the TER of human advisors is approximated to 1.5%. This leads to an average gap in terms of returns between a robo-advised strategy and a traditional one of roughly 4.4% per year, when a portfolio of 60% equity and 40% bonds is considered.

Finally, the third competitive advantage of robo-advisors is the absence of behavioral biases. The performance of individuals investing in stocks is often lowered by poor market timing and behavioral biases, such as overconfidence, mood, and emotion (see, e.g., Kahneman, 2011). The home bias can also be relevant. A digital advisor does not suffer from such behavioral biases because it strictly and automatically rebalances its assets when the market rises or falls and makes better use of the available data than the average investor.

2.3. Robo-advisor drawbacks

Several studies in the literature are rather critical of the simplicity and the lack of sophistication of automated financial advisors. Among others, Tertilt and Scholz (2018) discuss the questionnaires used to define a client's attitude towards risk. In their sample of German, U.S., and English robo-advisors, they show that these ask clients an average of 10 questions, but only 60% of the answers have a real impact on profiling. The algorithm that classifies clients into different risk profiles turns out to be too simplistic. In any case, digital advisors tend to propose conservative strategies with low-risk exposure. Moreover, they describe some variability in the composition of the proposed portfolios (for the same risk tolerance) depending on the robo-advisor's country. For example, U.S. digital advisors appear to create portfolios with a relatively high proportion of equities compared to German robo-advisors, especially for risk-averse clients. Boreiko and Massarotti (2020) draw similar conclusions. As a result, Tertilt and Scholz (2018) argue that at present, robo-advisors lack in their ability to categorize clients into different risk profiles and in the quality of their portfolio recommendations. Before replacing human asset managers, robo-advisors will have to improve their algorithms by using artificial intelligence and big data to create truly personalized portfolios, we discuss this in more detail in Section 3. Digital advisors will also have to significantly expand their investment universe, which is still currently limited to ETFs.

The March 2016 Financial Industry Regulatory Authority (FINRA) report discusses many other critical points of digital advisors. First, the report reiterates that robo-advisors do not provide truly personalized investment advice. Users are often left alone to determine whether the investment strategy offered by the machine is truly relevant to their needs. Digital advisors turn out to be tools that allow customers to determine their own risk tolerance and investment preferences. These tools, then, allow the customer to subscribe to a recommended asset allocation for investors with similar preferences. Thus, it would be a mistake for investors to believe that digital advisors perfectly meet their real financial needs. Second, the FINRA report mentions that robo-advisors do not eliminate conflicts of interest and could even make them worse. Pertaining to this concern, Fein (2015) shows that digital advisors use affiliate brokers, who may not offer the best price for customers. The profit resulting from this mechanism would be particularly high for robo-advisors who, on the contrary, insist on their low costs. The conflicts of interest found in the traditional financial industry can therefore also be found in automated financial advice.

Jung, Glaser, and Köpplin (2019) also call into question the fiduciary duty of digital advisors, i.e., their legal duty to act in the best interest of the client. Based on Fein (2015), the authors note that robo-advisors give very little consideration to client idiosyncrasies or other external factors that could have serious consequences in the event of an extreme market decline. Fein (2015) concludes that robo-advisors are not meeting their fiduciary duty and that only well-trained portfolio managers can effectively manage portfolios.

Finally, Schwinn and Teo (2018) highlight the fact that digital advisors are subject to country-specific regulations in terms of investor protection, compliance requirements, and taxation rules. Such burdens have an impact on the geographic extension of automated advisory (especially in Asia) and make it difficult to attract international investors.

In conclusion, all of the above-mentioned aspects demonstrate that human portfolio managers still have remarkable advantages over automated advisors to date. Table 1 below summarizes the above detailed advantages and disadvantages of robo-advisors.

Advantages	**Disadvantages**
Asset management without human intervention	Investor left alone to decide among different strategies
Customization of portfolio strategies	Strategies come from other (similar) investors
Investor's risk profile considered in portfolio optimization	Simplistic questionnaires for investor profiling
Specific investors targeted	Conservative strategies based on ETFs, not always tailored
Wide range of investors	Low fiduciary duty on investors' idiosyncrasies
Cheap passive portfolio strategies	Conflicts of interest affecting strategy costs
Absence of behavioral and home bias	Country-specific strategies beyond investor's profile
Optimized after-tax returns and tax loss harvesting	Limitations from country-specific regulations

Table 1. Main advantages and disadvantages of robo-advisors with respect to human advisors.

3.0 Big data and artificial intelligence in robo-advisory

In this section, before discussing the impact of big data analytics in automated asset management, we first spend some time discussing the possibilities of humanizing robo-advisor platforms. Then, we focus on the personalization of the digital financial advice via big data and, finally, we discuss the related algorithms implemented by robo-advisors.

3.1 Humanization inspired by artificial intelligence

An interesting issue for the success of digital advisory is the humanization of robo-advisors. The problem has its root in technological contexts, where artificial intelligence moderates the interaction between the machine and the user.

Several researchers question whether robo-advisors will be able to replace humans, or whether a hybridization of portfolio management will be more likely. For example, Hodge, Mendoza, and Sinha (2021) ask whether giving a robo-advisor a human name will encourage investors to use it. They start from the observation that this practice is increasingly common in the field of new technologies as, for instance, Apple named its virtual assistant *Siri*. Previous research into human-machine relationships has focused on simple interactions that any human could perform: asking Siri about the weather forecast is a relatively simple task. Conversely, financial consulting is more complex, and it is usually delegated to a professional. The existing literature on human-computer relationships may thus not apply in the case of digital advisors.

Interestingly, Hodge, Mendoza, and Sinha (2021) find that investors are more likely to trust a robo-advisor with a name than one without a name when the robot is performing a simple task. Nevertheless, the opposite is true when the robot is required to perform a difficult task. As a result, the benefits of robo-advisor humanization are still under discussion. Other ways to humanize robots may be considered, such as the use of avatars. In addition, the influence of other variables may be taken into account, including the investors' age and the gender attributed to the robot by its chosen name.

3.2 Big data for robo-advisor customization

As we already mention in the previous paragraphs, a fundamental feature for the current and the future success of automated asset management is customization, meaning the personalization of the provided financial advice to the client's specific needs. In this regard, Fisch, Labouré, and Turner (2019) document the increasing diversification of services offered by digital advisors, many of which are offering new services that target particular cohorts of customers. For example, since women have a higher average life expectancy than men, the robo-advisor Ellevest offers different portfolios based on the client's gender. In addition, the robo-advisor True Link focuses on older investors as well as retirees. These kinds of customization are rather basic and do not exhaust the potential of automated consulting. The crucial point is the way in which digital advisors acquire and exploit investors' information. A fundamental contribution in this direction will be made through the exploitation of big data and artificial intelligence in the coming years.

For the purpose of this study, we rely on the definition of big data's 3Vs (i.e., volume, velocity and variety) provided by Laney (2001). The amount of data, the volume, is often related to the number of concerned individuals, the observation frequency, and the number of observed features. The speed, or velocity, relates to data collection, data processing and their respective update. The variety refers to the heterogeneous nature of the data (quantitative, qualitative, longitudinal, textual data and so on). Some examples are given by credit card purchases, financial transactions, online searches on search engines, activity on social networks, location data, and so forth. The use of big data is pervasive in almost all industrial and service sectors. Interestingly, Xu (2021) mentions robo-advisors as an application of big data in the financial industry, in addition to risk control, customer value management, strategic marketing, credit risk assessment and many others.

Faloon and Scherer (2017) shed some light on the quality of the investor information captured via the questionnaires and the ways in which such information is exploited in portfolio optimization, keeping in mind the client's investment goals. Some of the variables considered by robo-advisors for customer profiling are listed in Table 3 of Jung, Gasler, and Kopplin (2019): income, investment horizon, liabilities, saving rate, age, gender, and degree of financial risk taken are some examples. Nonetheless, the conclusion of Faloon and Scherer (2017) is that robo-advisors are still far from providing customized investment solutions as they are still poorly individualized, a problem which can be mitigated by using the information extrapolated from big data. As we discuss in the next section, multiple integrations of big data in digital advisory can be fruitful. Textual data coming from the client's interaction with a chatbot can improve the effectiveness of questionnaires in profiling, even though there are current privacy issues concerning the storage of conversational data. Updated data about other investors' opinions and past choices can be clustered to recommend suitable investment solutions. Real-time information from social network activity can be also exploited.

In a 2020 article for Forbes, Koksal reports the words of John Zhang, founder of the robo-advisor WealthGap, which unravel the forthcoming role of big data in automated financial advisory: "[The] analysis of vast quantities of historical and financial data will uncover alpha opportunities that traditional analysis would otherwise overlook and give robo-advisors an edge over passive strategies and AI can process big data swiftly, allowing robo-advisors to adapt to changing market conditions and consumer behaviors much quicker in order to make better investment decisions. Time saved is key here".

3.3 Opening the black box

Xing, Cambria, and Welsch (2019) present two ways to increase robo-advisors customization via big data: dialogue systems and recommendation systems.

Dialogue systems include task-oriented systems and chatbots. The use of conversational data provided by chatbots is certainly promising for automated asset management. However, some concerns cannot be overlooked, client privacy and data processing costs are both significant issues. In addition, chatbots usually require a long interaction with the machine (a long dialogue history) to trigger the learning from textual data, which is not always feasible. The ultimate goal is to obtain a personalized dialogue system where the chatbot elicits the clients' personality through regular interaction with them (see, e.g., Fung et al., 2016). This can be achieved by using some given personality models that allow it to grasp the user's attitude towards risk or uncertainty.

An illustration of the functioning of chatbots is found in Chen, Liu, Yin, and Tang (2017). As opposed to task-oriented dialogue systems, chatbots can hold a conversation with the user on diversified topics. Chatbots based on generative models can produce appropriate replies that have never appeared before. Among them, sequence-to-sequence models associate a response sequence (in words) to a given input sequence (always in words) through an encoder-decoder structure with a hidden context. The encoder uses a recurrent neural network to read the input sequence and map it into a context vector, while the decoder maps the context vector to the response sequence, also through a recurrent neural network. An optimization problem is solved to determine the most likely appropriate answer. Day, Lin, and Chen (2018) have recently attempted to integrate conversational data in the asset allocation model of digital advisors. The authors introduce a knowledge-based and generative-based dialogue system into the robo-advisor architecture in order to moderate the interaction via a sequence-to-sequence model.

Robo-advisors can design multiple investment strategies and assign whichever is best suited to the client based on their investment targets and risk tolerance; this is referred to as a recommendation system. To determine suitable products, the system exploits the customer's personal information and previous investment choices, as well as the behavior of other investors with similar profiles and their opinions. In these steps, big data is essential, and numerous machine learning methods serve as effective tools. Unsupervised learning methods (e.g., k-means or agglomerative clustering) allow one to find groups of observations with homogeneous features, while principal component analysis helps with dimension reduction. Supervised learning methods (e.g., random forests, artificial neural networks and many others) are useful for classification and regression problems (see, for instance, James, Witten, Hastie, and Tibshirani, 2013). These tools allow for customers' profiling and segmentation. Xue, Zhi, Liu, and Yin (2018) design a robo-advisor that exploits investors' social relations and provides group recommendations based on financial social networks.

As described by Schwinn and Teo (2018), a successful example of the use of big data and artificial intelligence in automated advisory is that of the the Asian mobile trading and investing service 8 Securities (now known as SoFi Hong Kong). The platform provided by this company has access to news and social media. The related mobile app is effectively a social trading portal, where trading information can be shared among peers. In 2016, the company introduced the robo-advisor Chloe. As reported on Finews.asia on August 1, 2016: "Powered by artificial intelligence and machine learning technologies developed in-house, Chloe will learn day by day as its user base and database grow to optimize goal-setting and portfolio matching for customers with different financial needs". By using machine learning techniques, Chloe becomes increasingly able to predict a client's investment targets and their desired savings. Moreover, the portfolio performance can be checked directly from the investor's smartphone. In doing so, SoFi can target millennials with fragmented wealth who, as opposed to high-net-worth investors, do not usually turn to financial advisors.

Finally, in addition to improving customization, big data can be directly incorporated in the optimization algorithms used by digital advisors. Beketov, Lehmann, and Wittke (2018) provide a list of the most popular portfolio optimization methods employed by robo-advisors. Modern Portfolio Theory turns out to be the most widespread framework for portfolio optimization still today. However, robo-advisors also implement numerous improvements of Markowitz (1952) to reduce extreme portfolio weight sensitivity and high data dependence, and to include higher moments, tail risks and various optimization constraints. A first attempt to exploit big data in this direction is given by Day, Cheng, and Li (2018). The robo-advisor proposed by them adopts the Black and Litterman (1992) approach, which includes the investor's subjective view on expected returns in the portfolio optimization problem. Such a subjective view is extracted from the analysis of big data from diversified sources, including the investor's characteristics, updated asset prices, financial forecasts and so on. A learning module from these sources is integrated in the overall architecture of the digital advisor.

4.0 Conclusion

In the previous sections we briefly discussed the advantages and the disadvantages of robo-advisors, a disruptive technology for the financial industry. Although digital advisors aim to provide cheap personalized investment solutions to a wide range of clients, existing literature highlights their limitations in reaching this goal. However, this technology can highly profit from the analysis and treatment of big data.

More work must be done to properly capture investors' preferences and behavioral peculiarities for the future development of automated advisory through big data analytics. As outlined by Jung, Dorner, Glaser, and Morana (2017), future robot-advisors are expected to provide truly customized investment solutions, in a fully automated way, by employing a widespread user-friendly technology. Moreover, Xing, Cambria, and Welsch (2019) acknowledge that the influence of investors' personalities on their perception of risk is largely overlooked by the dialogue systems that aim at modeling them.

Other improvements are also expected in the functioning of dialogue systems. For instance, Chen, Liu, Yin, and Tang (2017) warn that conversational data on specific domains can be scarce. Dialogue agents should be able to autonomously learn, and elaborate concepts extracted from the web and become smart tools that rely less on repetitive training. Another delicate aspect to be managed is privacy protection, because many clients interact with the same dialogue agent and confidentiality must be granted.

Quantitatively, we expect the use of advanced machine learning and optimization methods by digital advisors to become widespread in the near future (Beketov, Lehmann, and Wittke, 2018). This approach meets the demands of investors, which are very demanding in terms of technology and sophistication. The marketing potential of such a quantitative direction is huge.

Finally, future developments in the exploitation of big data for automated advisory must address the issue of unfairness and bias in machine learning algorithms. As illustrated by Mehrabi et al. (2021), important biases can be present in the human-created sample data used for training the algorithms. The algorithms can amplify such distortions and produce biased outcomes. When financial and social network data are integrated into digital advisors, such biases need to be taken into account to avoid inappropriate investment decisions. Mehrabi et al. (2021) list some possible ways to mitigate this problem in many contexts, but the search for effective solutions is not over.

Financial or social network big data can largely improve the personalization of digital advisory in terms of customers' profiling and investment solution recommendation. Conversational data generated from the clients' interaction with a chatbot can help elicit their personality and financial needs. In addition, sophisticated machine learning methods integrated in the portfolio optimization algorithms used by digital advisors are promising tools for the future of financial consulting.

References

Beketov, M., Lehmann, K., & Wittke, M. (2018). Robo advisors: quantitative methods inside the robots. *Journal of Asset Management*, 19(6), 363–370. https://doi.org/10.1057/s41260-018-0092-9

Benson, A. (2022, February 28). 11 best robo-advisors of March 2022. *Nerdwallet. https://www.nerdwallet.com/best/investing/robo-advisors*

Black, F., & Litterman, R. (1992). Global portfolio optimization. *Financial Analysts Journal,* 48(5), 28–43. https://doi.org/10.2469/faj.v48.n5.28

Boreiko, D., & Massarotti, F. (2020). How risk profiles of investors affect robo-advised portfolios. *Frontiers in artificial intelligence*, 3, article 60. https://doi.org/10.3389/frai.2020.00060

Chen, H, Liu, X., Yin, D., & Tang, J. (2017). A survey on dialogue systems: Recent advances and new frontiers. *ACM SIGKDD Explorations Newsletter,* 19(2), 25–35. https://doi.org/10.1145/3166054.3166058

Day, M.-Y., Cheng, T.-K., & Li, J.-G. (2018). AI robo-advisor with big data analytics for financial services. In *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)* (pp. 1027–1031). IEEE. https://doi.org/10.1109/ASONAM.2018.8508854

Day, M.-Y., Lin, J.-T., & Chen, Y.-C. (2018). Artificial intelligence for conversational robo-advisor. In *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)* (pp. 1057–1064). IEEE. https://doi.org/10.1109/ASONAM.2018.8508269

Faloon, M., & Scherer, B. (2017). Individualization of robo-advice. *The Journal of Wealth Management*, 20(1), 30–36. https://doi.org/10.3905/jwm.2017.20.1.030

Fama, E.F., & French, K.R. (2010). Luck versus skill in the cross-section of mutual fund returns. *The Journal of Finance,* 65(5), 1915–1947. https://doi.org/10.1111/j.1540-6261.2010.01598.x

Fein, M. (2015). Robo-advisors: A closer look. *Available at SSRN*. http://dx.doi.org/10.2139/ssrn.2658701

Finews.Asia (2016, August 1). Hong Kong robo-advisor set to democratise global investing. *https://www.finews.asia/finance/22726-robo-advisor-fintech-asia- 8-securities*

FINRA (2016). Report on digital investment advice. https://www.finra.org/sites/default/files/digital-investment-advice-report.pdf

Fisch, J., Laboure, M., & Turner, J. (2019). The emergence of the robo-advisor. In J. Agnew & O. S. Mitchell (Eds.), *The disruptive impact of FinTech on retirement systems* (pp. 13–37). Oxford University Press. https://doi.org/10.1093/oso/9780198845553.001.0001

French, K.R. (2008). Presidential address: The cost of active investing. *The Journal of Finance,* 63(4), 1537–1573. https://doi.org/10.1111/j.1540-6261.2008.01368.x

Fung, P., Dey, A., Siddique, F., Lin, R., Yang, Y., Bertero, D., Wan, Y., Chan, R., & Wu, C.-S. (2016). Zara: a virtual interactive dialogue system incorporating emotion, sentiment and personality recognition. In *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: System Demonstrations* (pp. 278–281). https://aclanthology.org/C16-2058

Hodge, F., Mendoza, K., & Sinha, R. (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

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning with applications in R*. Springer. https://doi.org/10.1007/978-1-4614-7138-7

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

Jung, D., Glaser, F., & Köpplin, W. (2019). Robo-advisory: Opportunities and risks for the future of financial advisory. In V. Nissen (Eds.), *Advances in consulting research* (pp. 405–427). Springer. https://doi.org/10.1007/978-3-319-95999-3_20

Kahneman, D. (2011). *Thinking, fast and slow.* Ferrar, Straus and Giroux.

Koksal, I. (2020, April 18). How AI is expanding the applications of robo advisory. *Forbes. https://www.forbes.com/sites/ilkerkoksal/2020/04/18/how-ai-is-expanding-the-applications-of-robo-advisory/?sh=77dcfdea55c3*

Laney, D. (2001). 3D data management: Controlling data volume, velocity and variety. *META group research note*, 6(70)

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77–91. http://www.jstor.org/stable/2975974

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021) A survey on bias and fairness in machine learning. *ACM Computing Surveys,* 54(6), 1–35. https://doi.org/10.1145/3457607

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

https://www2.deloitte.com/content/dam/Deloitte/de/Documents/financial-services/Deloitte-Robo-safe.pdf

Nicoletti, B. (2017). *The future of FinTech. Integrating finance and technology in financial services*. Palgrave Macmillan, Springer. https://doi.org/10.1007/978-3-319-51415-4

Phoon, K., & Koh, F. (2018). Robo-advisors and wealth management. *The Journal of Alternative Investments,* 20(3), 79–94. https://doi.org/10.3905/jai.2018.20.3.079

Schwinn, R., & Teo, E. (2018). Inclusion or exclusion? Trends in robo-advisory for financial investment services. In *Handbook of blockchain, digital finance, and inclusion, Volume 2* (pp. 481–492). Elsevier. https://doi.org/10.1016/B978-0-12-812282-2.00021-8

Sharpe, W. (1991). The arithmetic of active management. *Financial Analysts Journal*, 47(1), 7–9. https://doi.org/10.2469/faj.v47.n1.7

Sironi, P. (2016). *FinTech innovation: From robo-advisors to goal based investing and gamification*. John Wiley & Sons.

Sovereign Wealth Fund Institute (2015, August 27). Everyone wants a robo-advisor, right? *https://www.swfinstitute.org/news/34448/everyone-wants-a-robo- advisor-right-8461344.*

Stulz, R. (2019). Fintech, bigtech, and the future of banks. *Journal of Applied Corporate Finance,* 31(4), 86–97. https://doi.org/10.1111/jacf.12492

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. https://doi.org/10.3905/jwm.2018.21.2.070

Uhl, M., & Rohner, P. (2018). Robo-advisors versus traditional investment advisors: An unequal game. *The Journal of Wealth Management,* 21(1), 44–50. https://doi.org/10.3905/jwm.2018.21.1.044

Weisser, C. (2016, July 28). The rise of the robo-adviser. *Consumer Reports*. *https://www.consumerreports.org/personal-investing/rise-of-the-robo-adviser/.*

Xing, F., Cambria, E., & Welsch, R. (2019). *Intelligent asset management*. Springer Nature Switzerland. https://doi.org/10.1007/978-3-030-30263-4

Xu, J. (2021). A comprehensive survey on applications of big data in the financial industry. In R. Thurasamy, I. A. Majid, N. A. B. A. Rahman & A. H. Zulkafli (Eds.), *Proceedings of the 2021 3rd International Conference on Economic Management and Cultural Industry (ICEMCI 2021)* (pp. 311–315). Atlantis Press. https://doi.org/10.2991/assehr.k.211209.053

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