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LNBIP 465

Digital Transformation

14th PLAIS EuroSymposium
on Digital Transformation, PLAIS EuroSymposium 2022
Sopot, Poland, December 15, 2022, Proceedings

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Lecture Notes in Business Information Processing 465

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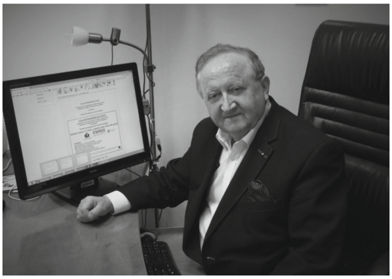
In Memoriam of Professor Stanislaw Wrycza (1949–2022) General Chair of EuroSymposia 2007, 2011–2021

Professor Stanisław Wrycza was a General Chair of the EuroSymposium conferences in 2007 and 2011–2021. In his research career, he was the head of the Department of Business Informatics at the University of Gdańsk (from 1991), the initiator and first president of the Polish Society for Information Systems (1995–2000), and president of the Polish Chapter of the Association for Information Systems (from 2006), among many other contributions. He was also recognized as an AIS Distinguished Member for demonstrated commitment to the Association for Information Systems (2021).



He was author and co-author of over 200 scientific publications, including over 40 books. He acted as a member of over 100 Program Committees of international conferences. He supervised over 20 doctoral dissertations and about a thousand master's and bachelor's theses. He organized many conferences, including ECIS 2002, BIR 2008, and numerous events in the EuroSymposia series.

Preface

The PLAIS EuroSymposium 2022 was organized with the leading topic of "Digital Transformation". The papers included in the proceedings are related to the use of machine learning, big data, and the Internet of Things in various applications. Other topics of the proceedings concern the current situation of ICT employees and their creativity via social media channels.

The objective of the PLAIS EuroSymposium 2022 was to discuss the general issues of digital transformation and related topics, as listed on the conference website. The EuroSymposia were initiated by Keng Siau, and previous EuroSymposia were organized by different academic institutions:

- University of Galway, Ireland: 2006
- University of Gdańsk, Poland: 2007
- University of Marburg, Germany: 2008
- University of Gdańsk, Poland: 2011–2021

The papers accepted for presentation at previous Gdańsk EuroSymposia were published in the following proceedings:

- 2nd EuroSymposium 2007: A. Bajaj, S. Wrycza (eds), Systems Analysis and Design for Advanced Modeling Methods: Best Practices, Information Science Reference, IGI Global, Hershey, New York, 2009
- 4th EuroSymposium'2011: S. Wrycza (ed.), Research in Systems Analysis and Design: Models and Methods, LNBIP 93, Springer, Berlin, 2011
- Joint Working Conferences EMMSAD/EuroSymposium 2012 held at CAiSE'12: I. Bider, T. Halpin, J. Krogstie, S. Nurcan, E. Proper, R. Schmidt, P. Soffer, S. Wrycza (eds.), Enterprise, Business-Process and Information Systems Modeling, series: LNBIP 113, Springer, Berlin, 2012
- 6th SIGSAND/PLAIS EuroSymposium'2013: S. Wrycza (ed.), Information Systems: Development, Learning, Security, Series: Lecture Notes in Business Information Processing 161, Springer, Berlin, 2013
- 7th SIGSAND/PLAIS EuroSymposium'2014: S. Wrycza (ed.), Information Systems: Education, Applications, Research, Series: Lecture Notes in Business Information Processing 193, Springer, Berlin, 2014
- 8th SIGSAND/PLAIS EuroSymposium'2015: S. Wrycza (ed.), Information Systems: Development, Applications, Education, Series: Lecture Notes in Business Information Processing 232, Springer, Berlin, 2015
- 9th SIGSAND/PLAIS EuroSymposium'2016: S. Wrycza (ed.), Information Systems: Development, Research, Applications, Education, Series: Lecture Notes in Business Information Processing 264, Springer, Berlin, 2016
- 10th Jubilee SIGSAND/PLAIS EuroSymposium'2017: S. Wrycza, J. Maślankowski (eds), Information Systems: Development, Research,

Applications, Education, Series: Lecture Notes in Business Information Processing 300, Springer, Berlin, 2017
- 11th SIGSAND/PLAIS EuroSymposium’2018: S. Wrycza, J. Maślankowski (eds), Information Systems: Research, Development, Applications, Education, Series: Lecture Notes in Business Information Processing 333, Springer, Berlin, 2018
- 12th SIGSAND/PLAIS EuroSymposium’2019: S. Wrycza, J. Maślankowski (eds), Information Systems: Research, Development, Applications, Education, Series: Lecture Notes in Business Information Processing 359, Springer, Berlin, 2019
- 13th SIGSAND/PLAIS EuroSymposium’2021: S. Wrycza, J. Maślankowski (eds), Information Systems: Research, Development, Applications, Education, Series: Lecture Notes in Business Information Processing 429, Springer, Berlin, 2021

The14th EuroSymposium, which took place on December 15, 2022, was organized by the Polish Chapter of AIS (PLAIS) and the Department of Business Informatics of the University of Gdańsk, Poland.

The paper submission and reviewing processes were supported by the new EquinOCS system hosted by Springer. Each submission was reviewed by at least two Program Committee members in a double blind manner. According to the review scores, eight papers were accepted for publication in this volume, giving an acceptance rate of 35%. The accepted papers are organized into three parts:

- Artificial Intelligence
- Creativity and Innovations
- Big Data, Internet of Things, and Blockchain Technologies

I would like to thank all authors, reviewers, and Program Committee and Organizing Committee members for giving us the opportunity to engage in high-level discussions on the topics of the conference. With their support, the PLAIS EuroSymposium2022 was a successful event.

This conference was organized in memoriam of Professor Stanisław Wrycza, who was a General Chair for many editions in the EuroSymposia series.

December 2022

Jacek Maślankowski
Bartosz Marcinkowski
Paulo Rupino da Cunha

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Contents

Artificial Intelligence

Sustainable Robo-Advisor Bot and Investment Advice-Taking Behavior

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Abstract. One of the main reasons why people use robo-advisors is that the traditional financial instruments (e. g. deposits, bonds) will promise zero returns in the near future. Robo-advisors using built-in algorithms to determine the assets of investment portfolios for short-run and long-run periods will be one of the promising options for the investor to obtain income in order to achieve his/her goals. Live Trading bots will be able to provide substantial passive in-come for investors, that is an attractive alternative, compared to the advice of traditional human advisors. The goal of this paper is to develop a robo-advisor bot to make investment decisions in order to choose the best financial instruments considering risk-return criterion using different investment strategies. The paper deals with the models of robo-advisor bot for different risk attitudes of investors. Each investor can choose among different investment strategies, such as buy-and-hold strategy, moving average strategy, relative strength index strategy, support and resistance strategy with different performance measures. All strategies dealing with risk-return criterion for precious metals demonstrate the greatest efficiency for risk-averse investors. RSI (relative strength index), buy-and-hold strategies are also effective for Netflix shares. Oil and cryptocurrencies are most appropriate for different strategies of risk-seeking investors. Tesla stock is the most appropriate for risk-neutral investors under definite period.

Keywords: Robo-advisor bot · Risk-return criterion · Investment strategy · Financial instruments

1 Introduction

H. Markowitz's Modern Portfolio Theory (MPT) is based on two main factors: risk and expected returns. In this case, an investor chooses a portfolio with the highest returns and the slightest danger. The investment goal is to get more profit with less risk [1]. Building a portfolio an investor can act in two possible situations: complete uncertainty (an investor can not determine scenario probabilities) and conditions of risk (probabilities can be determined). Nowadays, to clarify the model we can add one additional factor – risk tolerance or risk aversion which is influenced by various factors and described by the Arrow-Pratt coefficient. It is valid only if an investor behaves rationally: he/she can

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calculate different scenarios, identify the utility, maximize benefits, always choose the best option among the alternatives.

However, even experienced investors often make controversial and sometimes wrong financial decisions, for example an undiversified portfolio or a risk concentration. C. Frydman and C.F. Camerer associate it with low level of financial literacy and managed funds popularity [2]. Moreover, we tend to see the main problem of investors' mistakes in cognitive constraints. According to D. Kahneman's research, the decisions made by economic agents usually differ from those made with the "homo economicus" model [3]. J.Y. Campbell insists that "households do not save and invest according to the normative models" [4]. Consequently, they "typically have underdiversified stock holdings and low retirement savings rates" [2]. De Bondt says that people forget the basic investment principles and laws when investing; they rely on intuition and other factors but not quantitative measures [5].

It is true not only for the private investors but for the experienced, financially literate managers as well: "even the top business managers, who are usually highly educated, make decisions affected by overconfidence and personal experience" [2]. And what is more, "even Markowitz, the creator of MPT, did not use MPT in his own portfolio choice" but he simply created a 50/50 mix of stocks and bonds [6]. The issues dealing with growing data volumes, lack of understanding information culture, low level of economic agents' financial literacy, cognitive constraints will intensify. Moreover, E. Bikas claims investing in financial markets is becoming more popular [7]. This requires the use of automated financial and investment decision-making tools.

Now there is a large number of software solutions for robo-advisors. Chatbot service is actively used and has already been implemented in many sectors for customer support. Let us consider an example of such a bot Erica (Fig. 1), offered by Bank of America. The bot was introduced in the end of 2018 and at the beginning of 2019, it had 6.3 million users and 16.5 million applications. This solution is built into the bank's mobile application; it involves the functions: sending notifications about banking alerts, identifying available opportunities to reduce costs, i.e. counseling customers and giving advice how to save money, notifying about credit rating changes and simplifying bill payments.

Further, we consider the Ally Assist bot (Fig. 2) launched in 2015 by Ally Bank. Ally Assist is a chatbot built into the Ally Mobile app that you can interact with using voice commands and text messages. The functions of the bot involve making payments, money transfers, P2P transactions and deposits. Also, the user can get information about the bank account or transaction history. Using Machine Learning (ML), Ally Assist can predict a user's needs through account and transaction analysis in order to provide relevant messages with recommendations. In addition, the bot uses Natural Language Processing technologies to answer frequently asked questions.

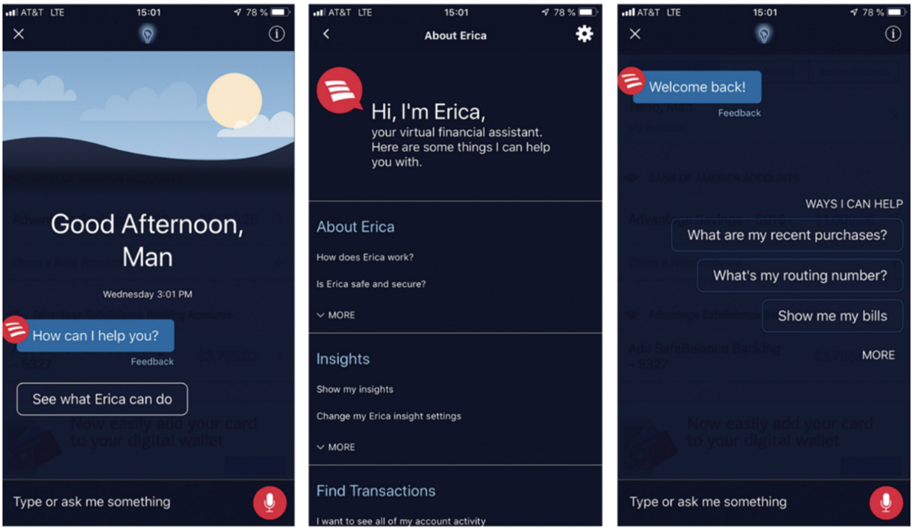

Fig. 1. Chatbot Erica.

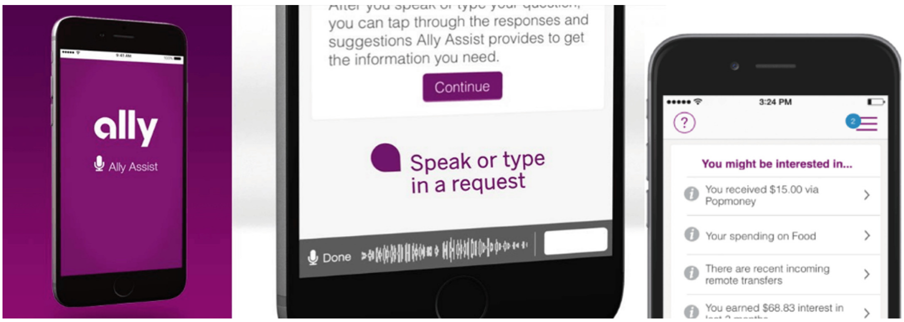

Fig. 2. Chatbot Ally assist.

Robo-advisors can be considered as an application. They provide affordable opportunities to invest and manage money in traditional models, allowing more people to save, invest and grow their capital to achieve financial goals. There are many examples of robo-advisors, but the best of them is Wealthfront (Fig. 3).

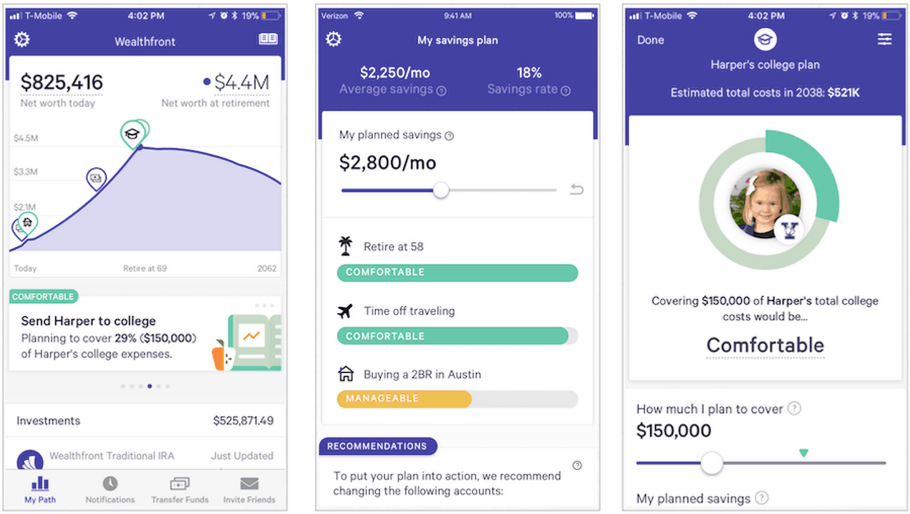

Fig. 3. Wealthfront robo-advisor.

Wealthfront offers an exceptional portfolio management experience and remains a digital, automated financial investment solution with an extensive suite of portfolio management tools and a wide variety of financial products.

As far as we know, there is high demand for robo-advice and possibility for investor to choose among different opportunities, but there are no platform or application to meet these requirements.

The **goal** of this paper is to develop a robo-advisor bot to make investment decisions in order to choose the best financial instruments considering risk-return ratio using different investment strategies.

The paper has the following structure: Sect. 2 considers the related works to the study. Sect. 3 presents the models of robo-advisor for the investor's different goals. Sect. 4 considers strategies of robo-advisor bot for different financial instruments. The last part concludes the paper.

2 Related Research

We use the economic, statistical and analog methods, the expert views to assess the financial risk. The economic and statistical methods assess financial risk using the following indicators: the average value of the investor's profit of random variables (risk factor); dispersion; standard deviation of a profit; semi-standard deviation; the coefficient of variation; probability distribution of a profit. The density function of a normal probability distribution allows us to calculate the probability of making a profit. Value at Risk (VaR) or "investment risk" is an integral measure of risk that can compare the risk of different investment portfolios and different financial instruments. VaR shows a confidence of x% (with a probability of x%) that the investor's losses will not exceed y monetary units over the next n days. In this statement, the value of y is unknown and is

VaR, which is a function of two parameters: the time horizon n and the confidence level x [8].

Characteristics of private and institutional investors' impact on the probability of using sustainable robo-advisors, and probability of use is 1.53 times higher among young and experienced investors. RAs use the mathematical algorithms and artificial intelligence in order to advise clients and reiterate human service. 'While people can be influenced by emotions, so it leads to wrong investment decisions, RAs claim to be bias free' [9]. COVID-19 pandemic was the first test for RA and this showed investors 'that online services are vital for investment purposes' using exchange traded funds (ETF) mostly.

The EU policy requirements to classify sustainable and non-sustainable investments and competition between RAs tend to ethical investing using the green investment in order to fight climate changes.

The authors [10] demonstrated that the investor's sustainable consumption 'transforms into a higher probability of choosing the portfolio according to a sustainable investment strategy', 'the sustainable consumers are more likely to select a green robo advisor that offers the sustainable investment strategies even though this requires higher management expenses' and 'socially responsible investment is an opportunity for investors to invest in accordance with their personal values'. At the same time, diversification of green investments portfolio is decreased and creates higher costs of RA.

According to the return perspective, it is important to distinguish conventional (not considering the impact of investments on the environment) or sustainable (e.g., return from green investments) investment decisions. It means a trade-off between social and financial returns depends also on the investors' utility preferences. It can be done by implementing smart algorithms and artificial intelligence tools.

We can define 3 different types of RA (Fig. 4) having distinguishing features (Table 1) [9].

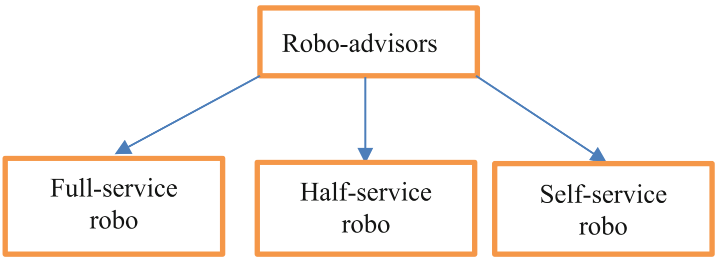

Fig. 4. Types of robo-advisors.

Investor's characteristics (male, age, education, cost awareness, ecological aspects) play a significant role for the probability of investing via a sustainable robo-advisory service, where mostly older persons prefer to use a sustainable robo-advisor [9].

RA provides with advanced estimation techniques employing artificial intelligence, but it still has the characteristic of being understandable. The investors who require more RAs assistance are less likely to use these services due to lack of trust. And for that

Table 1. Types, goals and characteristics of RA.

Types of RA	Characteristics of RA	Goal
Full-service robo (robo-managers)	Monitoring the robo-advisor's business for investor protection Sequential recommendations to meet the complex and dynamic investment requirements Reallocations in investment portfolios	Automated portfolio management service (automated decision making) in long-run period (more than 10 years)
Half-service robo (traditional of hybrid)	Always require the investor's consent to execute orders; The percentage weight can vary; the offensive share is stated by stocks whereas the defensive aspects refer to conservative investments such as bonds Only a portfolio suggestion is after an initial conversation with a human financial advisor	The provision of investment proposals robo-advisor does not hold a mandate to autonomously execute orders but rather acts as an investment intermediary in middle period (5–10 years)
Self-service robo	Self-service-robo neither executes an order, nor opens a securities account An information source is used to gain investment proposals To gain additional information or investment proposals for verification purposes freedom of choice contributes to the high level of autonomy of investors	To provide information to an investor thereby assisting in the decision-making process to independently manage the portfolio in short-run period (1–3 years)

reason, many stakeholders (investors, consumers, regulators and supervisory authorities) need to understand not only benefits of financial advice, but also the process itself and its implications in order to trust these recommendations [11].

RA firms 'rely on algorithmic trading strategies that can be made automatically, without hardly any human decisions in the process' [12]. There are qualitative and quantitative differences between RA within and across different countries (the USA, the UK, the EU). 'The aim of the qualitative analysis is to use the predefined criteria to gain a better understanding of the heterogeneity of the RAs approach to portfolio selection and subsequent portfolio management' [12]. The qualitative criteria in the fields of law, economics, and computer science are described in Table 2.

Table 2. Robo-advisors qualitative criteria.

Qualitative criteria	Description of criteria	Comments (examples)
Type of RA	Information about unique nature of business model of RA and its algorithms	White paper of RA
Amount of assets under management (AUM)	A *time series database* has to be generated	Markets of the USA, the UK, Germany from the largest till the smallest AUM
Investment portfolio data availability	Data retrieval and processing about financial instruments (e.g., shares, ETF, cryptocurrencies, real estate, precious metals, currencies, commodities)	Open data: https://finance.yahoo.com, https://www.ariva.de
Country-specific regulatory requirements	Different taxation, fees, minimum investment amount	Fee from 0 till 2.5% of AUM
Numbers of risk classes	Risk classes: low, medium and high risk levels	There are from 3 till 23 risk classes
Type of required portfolio rebalancing	Rebalance it if a certain threshold value is exceeded	As a rule, threshold or trigger value changes between 3% and 20%

Finally, the investment decisions can be attributed to a number of different factors [13]. The essence of the concept is that the financial instruments of the investment portfolio should be diversified in different terms, types and modifications issued by corporations in different industries and geographical locations [14].

The optimization model and the optimization formula lists include quantitative criteria and performance measures to develop portfolio design and evaluate financial benefits correspondingly (Table 3). The larger Sharp ratio, VaR ratio, Sortino ratio the more successful is an investment strategy. $\bar{r}$ is a portfolio return, r_f is a risk-free interest rate, r_z is an affordable risk level, σ_p is a standard deviation of portfolio, VaR_{CL} means VaR of a certain confidence level. The differences between the RAs relate the specific company, they are driven by the business model and focus on a specific investor's needs.

'Algorithmic advice refers to the automation of professional advice giving by expert systems interacting with consumers instead of highly trained specialists', because the investors who believe that AI is more capable than human intelligence are more likely to adopt algorithmic advice of RA [15]. 'Algorithm aversion is higher when human uniqueness is of great relevance and the tasks are intuitive, subjective but they are not quantifiable and objective' and 'consumers believing that AI is more capable than human intelligence will only be more likely to adopt algorithmic advice when perceived task complexity is high' [15]. The studies on AI advice suggest that getting maximum accuracy in decision-making is a main incentive for investors to use RA. FinTech managers

Table 3. Performance measures for investment portfolio.

Performance measures	Formula
Simple annual return $\bar{r}$	$\bar{r} = \frac{\sum_{i=1}^{n} r_i}{n}$
Annual volatility σ_p	$\sigma_p = \frac{\sum_{i=1}^{n}(r_i - \bar{r})^2}{n}$
Annual VaR $VaR_{annual}^{95\%}$	$VaR_{annual}^{95\%} = (5\% - quantile(r_i) + 1)^{12} - 1$
Maximum drawdown MD	$MD = -minimum\left(vector\left(\frac{\Pi_i(1+r_i)}{cummul\, max \Pi_i(1+r_i)} - 1\right)\right)$
Sharp ratio SR_p	$SR_p = \frac{r_p - r_f}{\sigma_p}$
VaR ratio VR_p	$VR_p = \frac{r_p - r_f}{VaR_{CL}}$
Sortino ratio SO_p	$SO_p = \frac{r_p - r_z}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}[\max(r_z - r_t; 0)]^2}}$

may divide the customers into segments according to different beliefs about AI and offer different types of investment and insurance advice to different segments of customers.

'The majority of consumers still express a preference for human financial advisors, because of RAs' lack of a "human touch" and a human ability to understand and personalize investment advice to the consumers unique financial situation' [16]. Thus, conversational as opposed to non-conversational RAs increase the probability for consumers to follow portfolio recommendations even if the advice is inconsistent with actual risk profile or includes larger annual fees. Conversational RAs (i.e., possessing dynamic, dialogue based, and turn-taking communication features) and nonconversational RAs (i.e., possessing static, self-report, and one-way communication features) have distinguishing features. Therefore, RA anthropomorphic design can influence positively on investor's service satisfaction and RA's performance; higher levels of affective trust in a conversational compared to a non-conversational RA increases investors' willingness to accept a recommended financial portfolio [16].

Decision support tool depends greatly on its usability and unwillingness to engage the manage investment questions with RA [17]. Requirements for RA's design principles consist of (1) ease of use (to ensure ease of interaction with the RA); (2) work efficiency (to support users' ability to achieve their goals in expected time); (3) information processing and cognitive overload (to assist users with information processing using video with simplified language of explanation); (4) advisory transparency (to provide disclosure of costs and assets). It is necessary to use different RAs designs to improve the services and user experience.

Financial mistakes made by inexperienced investors, 'who are the largest part of the population, vary for different individuals (e.g., a person has low statistics skills) and in different situations (e.g., stress, cognitive overload)', therefore, inexperienced investors need a good decision support [18]. Multi-modal monitoring includes measurement of users' physiological states (e.g., arousal or cognitive load). It helps to assess the user internal states, incentives and risk attitude.

It means to examine how develop the optimal design of a robo-advisor for guaranteed income estimator for the investor using risk premium under acceptable financial risk. RA can provide such advice to the investors about different portfolios with less or no risk.

Discretion is an investors' ability to override robo-advisors' recommendation, 'robo-advisors that allow for more discretion let investors modify the portfolio weights the algorithm proposes' [19]. Investors can also choose whether proposed algorithm recommendations should be implemented or changed manually. However, to the best of our knowledge, a robo-advisor has no built-in insurance premium module to create incentives for investors to start investing.

3 Models of Robo-Advisor for Different Goals of Investor

The client's risk profile and investment goals are determined before the investment process. In other words, it is what goal the person wants to achieve by the means of the investments in the time horizon. The investor should answer some questions. The answers form the basis for his/her psychological and investment characteristics, it highlights the risk propensity. He/she is also asked to determine the particular investments goals (e.g. to buy a new house, to save money for children's education), because "people have different mental accounting for each investment goal, and the investor is willing to take different levels of risk for each goal" [20]. However, it is suggested to choose not only the primary goal, but also several additional ones. Investors' characteristics can be used to determine the clusters of investors [21]. Diversification, i.e. the using of various investment instruments for different sectors of the economy, occurs not only for one investment portfolio but also for several investment portfolios based on the person's specific goals.

According to the goal, an investor may have a different attitude to risk:

- risk aversion with risk minimization (investors not inclined to take risks of retirement savings);
- risk seeking with return maximizing (investors inclined to take risks launching a startup);
- risk neutral with a desire to achieve minimum risk with maximum return (investors neutral to take risks of savings for a new home).

In addition to profitability, an investor also has to consider the risk associated with the portfolio of financial instruments. According to the Markowitz model, the risk is expressed as the standard deviation σ_p of each financial instrument. The σ_p value is the level of acceptable portfolio risk for the investor. Also, considering the standard deviation of financial instruments, it is necessary to analyse the correlation between profitability of different financial instruments r_{ij}. As a result, we can present the risk of the entire portfolio by the formula (1), where X – matrix of finance instruments' shares, X' – transposed matrix, V^2 – matrix of variations of financial instruments, V_{ij} – matrix of covariations:

$$\sqrt{X^2V^2} + X'V_{ij}X = \sigma_p \tag{1}$$

The mathematical model for optimal portfolio of financial instruments for an aggressive investor with maximum efficiency $M_p = R'X$, in which the portfolio risk does not exceed a given value σ_p, and considered all restrictions on the portfolio, has the following form (R' - transposed matrix of profitabilities of financial instruments):

$$\begin{cases} M_p \to max; \\ \sigma_p = const; \\ \sum_{i=1}^{n} x_i = 1; \\ x_i > 0, i = 1, \ldots, n. \end{cases} \tag{2}$$

The inverse problem in portfolio optimisation relates to the choice of the portfolio structure with higher or equal expected return M_p with minimal risk σ_p. Consequently, we create a portfolio for a conservative investor. In this case, the mathematical model for the problem has the form:

$$\begin{cases} \sigma_p \to min; \\ M_p = const; \\ \sum_{i=1}^{n} x_i = 1; \\ x_i > 0, i = 1, \ldots, n. \end{cases} \tag{3}$$

Developing a portfolio for a risk-neutral investor, risk minimisation and profit maximisation are simultaneously occured. Thus, we receive the following mathematical model for the problem (4):

$$\begin{cases} \frac{\sqrt{X^2V^2} + X'V_{ij}X}{R'X} \to min; \\ \sum_{i=1}^{n} x_i = 1; \\ x_i > 0, i = 1, \ldots, n. \end{cases} \tag{4}$$

Next, we consider the architecture of a Robo-advisor based on open data about currency of crypto assets (Fig. 5) for drawing up investment plans [22–25].

In the research, we can choose the cryptocurrency funds since they have low correlation to traditional assets, such as gold or stocks. The cryptocurrency funds can be used for portfolio diversification and creating the independent investment portfolio for a risk-averse investor using advantages investing in commodities and currencies in the financial market [26].

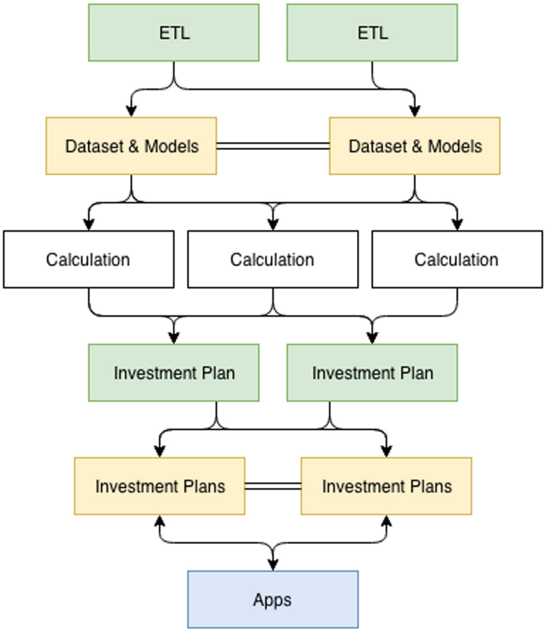

Fig. 5. Architecture of a robo-advisor.

4 Strategies of Robo-Advisor Bot for Different Financial Instruments

Completing an experiment, a software robo-advisor bot was developed using Python Anaconda and Python Jupyter technology. In its final form our robo-advisor (RA) has the architecture shown in Fig. 6 [20].

The customer has to register or, if he/she is already registered, enter the service on the website or in application. The advantage of the developed application is a short registration procedure without gathering confidential information. All you need if you want to register is to confirm your mobile phone number, and then you are given 3 days to use and test the robo-advisor at demo account. Next, the user has an opportunity to choose one of the investment plans based on personal preferences. All investment portfolios are divided into 3 categories: low, medium and high-risk attitude. After choosing one of them, several investment plans become available to customer. In this application customer can find various services, ranging from creating a diversified investment portfolio to purchasing the services of robo-advisor, which trade automatically on platforms (e.g. Binance) in real time. Using any product, client can see in real time all the operations performed by the bot, open and closed transactions, the time and date of transaction closing, purchase and sale of any financial instrument.

Each investor can choose different investment strategies. The most effective of them are:

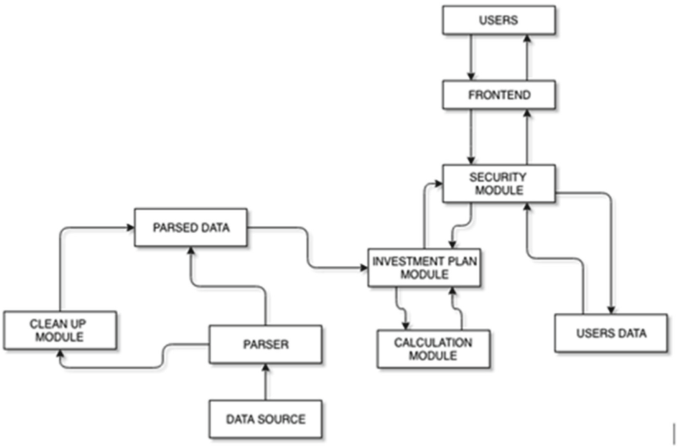

Fig. 6. Architecture of a robo-advisor bot.

1) Buy-and-Hold strategy means purchasing of undervalued financial instruments and their sale at the peak of the market.
2) Moving average (MA) strategy is the purchase/sale of financial instruments when the trend changes, as indicated by the intersection of moving averages for the short-run, long-run, and medium-run periods.
3) Relative strength index (RSI) strategy determines the signal to buy/sell, when the indicator has touched the level 30% (70%) or it is in the oversold/overbought zone, the MACD indicator is above/below the zero level.
4) Support and resistance strategy determines the extremes of the financial instrument price, defining the entry/exit points on the market.

Let us consider the performance of the developed robo-advisor bot. To begin with, it is necessary to determine the closing days and limits of purchase/sale of financial instruments for various strategies (Fig. 7). Thus, when the price of a financial instrument falls to 70% of the initial value, a sale occurs. When the price increases by 30%, compared to the initial value, an automatic sale of the financial instrument happens.

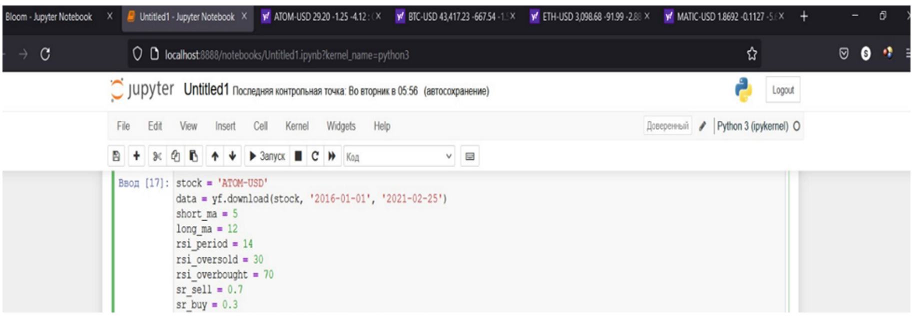

Fig. 7. Algorithmic trading limits for buying and selling financial instruments (code snippet).

After that, data about the closing price of the financial instrument in a specified period are collected and the necessary parameters for calculating the rate of return and risk of this asset are determined using metrics of return and risk from previous Sect. 3 (Fig. 8).

```
data['MA' + str(short_ma)] = data['Close'].rolling(short_ma).mean()
data['MA' + str(long_ma)] = data['Close'].rolling(long_ma).mean()
data['return'] = data['Close'].pct_change()
data['Up'] = np.maximum(data['Close'].diff(),0)
data['Down'] = np.maximum(-data['Close'].diff(),0)
data['RS'] = data['Up'].rolling(rsi_period).mean()/data['Down'].rolling(rsi_period).mean()
data['RSI'] = 100 - 100/(1 + data['RS'])
data['S&R'] = (data['Close']/(10**np.floor(np.log10(data['Close']))))%1
```

Fig. 8. Formulas for calculating rate of return and risk of financial instruments (code snippet).

Next step is preparation of signals' description for buying/selling financial instruments and setting trading frameworks (Fig. 9). These signals are the triggers for algorithm to buy/sell financial instruments when prices decrease/increase by 70%/30% compared to the initial value.

```
BnH_return = np.array(data['return'][start+1:])
MACD_return = np.array(data['return'][start+1:]) * np.array(data['MACD_signal'][start:-1])
RSI_return = np.array(data['return'][start+1:]) * np.array(data['RSI_signal'][start:-1])
SR_return = np.array(data['return'][start+1:]) * np.array(data['S&R_signal'][start:-1])
```

Fig. 9. Description of buy/sell signals for financial instruments (code snippet).

The next step in the chat bot is the calculation of the investor's income from the buying/selling financial instrument using various strategies during definite period (Fig. 10):

```
BnH = np.prod(1+BnH_return)**(252/len(BnH_return))
MACD = np.prod(1+MACD_return)**(252/len(MACD_return))
RSI = np.prod(1+RSI_return)**(252/len(RSI_return))
SR = np.prod(1+SR_return)**(252/len(SR_return))
```

Fig. 10. Calculation asset returns for different investment strategies.

Next, we calculate the risks for various strategies, based on the closing price of financial instruments of previous periods using formula of standard deviation of the samples (Fig. 11).

```
BnH_risk = np.std(BnH_return) * (252)**(1/2)
MACD_risk = np.std(MACD_return)* (252)**(1/2)
RSI_risk = np.std(RSI_return) * (252)**(1/2)
SR_risk = np.std(SR_return) * (252)**(1/2)
```

Fig. 11. Calculation of the risks level of the asset under various investment strategies.

Based on all the obtained results, we made forecasts using our robo-advisor bot for the following period (month) for specified financial instruments using different strategies (Fig. 12).

```
print('доходность и риск стратегии Buy-and-Hold ' + str(round(BnH*100,2))+'% и ' + str(round(BnH_risk*100,2)) + '%')
print('доходность и риск стратегии скользящих средних ' + str(round(MACD*100,2))+'% и ' + str(round(MACD_risk*100,2)) +
print('доходность и риск стратегии RSI ' + str(round(RSI*100,2))+'% и ' + str(round(RSI_risk*100,2)) + '%')
print('доходность и риск стратегии поддержка и сопротивление ' + str(round(SR*100,2))+'% и ' + str(round(SR_risk*100,2)

доходность и риск стратегии Buy-and-Hold 133.91% и 81.97%
доходность и риск стратегии скользящих средних 156.57% и 81.92%
доходность и риск стратегии RSI 63.66% и 49.85%
доходность и риск стратегии поддержка и сопротивление 85.59% и 67.73%
```

Fig. 12. Comparison of profitability and risks for different investment strategies of the specified financial instrument

Our developed software: (https://drive.google.com/drive/folders/1ks5duDulG3HsuNONzm-nCmhpjqKcWkZi?usp=sharing) allows automatically computing the profitability and risk of defined financial instruments using different investment strategies choosen for the investor goals.

Let us consider the return and risk of investing in precious metals: gold stock = 'GC = F', silver stock = 'SI = F', nickel ^N225 by the means of the developed robo-advisor bot (Table 4).

Table 4. Indicators of profitability and risk of investing in precious metals.

Financial instrument	Strategy	Return/risk
Gold	Buy-and-Hold	110.21%/14.82%
	Moving average	94.37%/14.83%
	RSI	96.84%/7.51%
	Support and resistance	106.76%/11.25%
Silver	Buy-and-Hold	114.46%/28.82%

(*continued*)

Table 4. (*continued*)

Financial instrument	Strategy	Return/risk
	Moving average	95.41%/28.84%
	RSI	94.44%/18.6%
	Support and resistance	123.81%/19.65%
Nickel	Buy-and-Hold	111.83%/20.1%
	Moving average	96.92%/20.12%
	RSI	96.92%/10.73%
	Support and resistance	100.24%/16.06%

In the next stage, we calculated the profitability and risk of investing in oil stock = 'CL = F' under different strategies (Table 5).

Table 5. Indicators of profitability and risk of investing in oil.

Financial instrument	Strategy	Return/risk
Oil	Buy-and-Hold	114.22%/155.92%
	Moving average	202.04%/155.75%
	RSI	nan*%/63.9%
	Support and resistance	146.55%/141.66%

* 'nan' means not announced.

For cryptocurrencies, we calculated the profitability and risk of investing in Ethereum (ETH-USD) and Cardano (ADA-USD) (Table 6).

Table 6. Indicators of profitability and risk of investing in cryptocurrencies.

Financial instrument	Strategy	Return/risk
Ethereum (ETH-USD)	Buy-and-Hold	133.91%/81.97%
	Moving average	156.57%/81.92%
	RSI	63.66%/49.85%
	Support and resistance	85.59%/67.73%
Cardano (ADA-USD)	Buy-and-Hold	216.57%/133.3%
	Moving average	243.89%/133.24%
	RSI	nan*%/97.49%

(*continued*)

Table 6. (*continued*)

Financial instrument	Strategy	Return/risk
	Support and resistance	123.63%/111.36%

* 'nan' means not announced.

For stocks, let's compute the return and risk of investing in Netflix, Inc. (NFLX), Tesla, Inc. (TSLA) (Table 7).

Table 7. Indicators of profitability and risk of investing in shares.

Financial instrument	Strategy	Return/risk
Netflix, Inc. (NFLX)	Buy-and-Hold	139.82%/40.63%
	Moving average	74.62%/40.7%
	RSI	104.02%/19.34%
	Support and resistance	98.53%/32.18%
Tesla, Inc. (TSLA)	Buy-and-Hold	177.19%/58.0%
	Moving average	125.42%/58.14%
	RSI	61.72%/39.97%
	Support and resistance	102.47%/45.72%

On the basis of various and diversified financial instruments, we consider the most attractive taking into account the "risk-return" criterion (Figs. 13, 14, 15 and 16). The lower this indicator is, the more investment-attractive the financial instrument is, since 1% of the return represents a lower investment risk. Risk-return criterion has the following form:

$$RRc = \frac{risk}{return} \tag{5}$$

For risk-averse investors all strategies according to the "risk-return" criterion for precious metals demonstrate the greatest efficiency. RSI (relative strength index), Buy-and-Hold strategies are also effective for Netflix shares. For risk-seeking investors all strategies include oil and cryptocurrencies. For risk-neutral investors Tesla stock is the most appropriate during addressed period. This list of financial instruments is obviously not exhaustive and the preferences of investors can include any other kinds of assets.

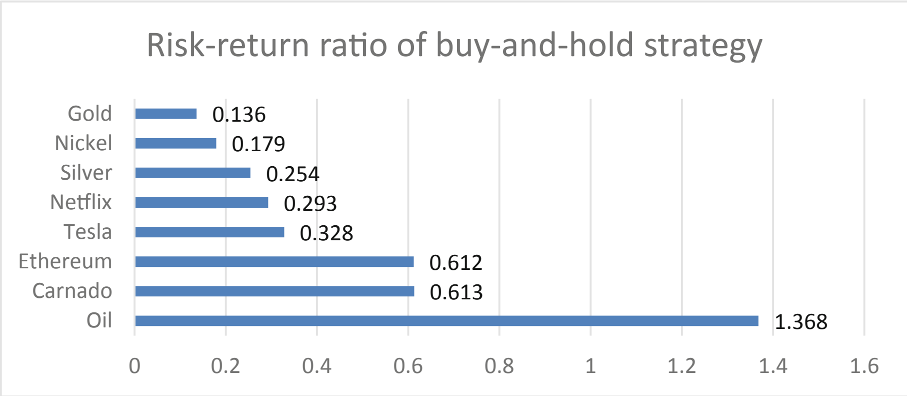

Fig. 13. Risk-return ratio of buy-and hold strategy

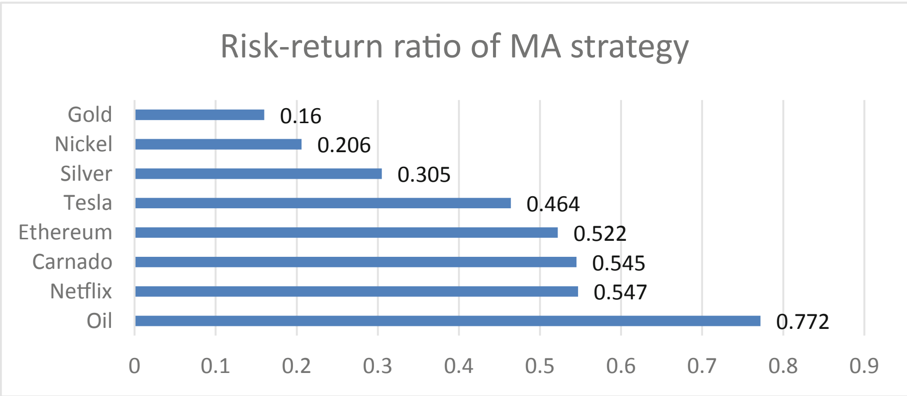

Fig. 14. Risk-return ratio of moving average strategy

In the future, we plan to expand the functions of robo-advisor chat-bot. We are trying to develop of a full-fledged mobile application and website, to expand the range of strategies for providing more convenient and reliable consulting.

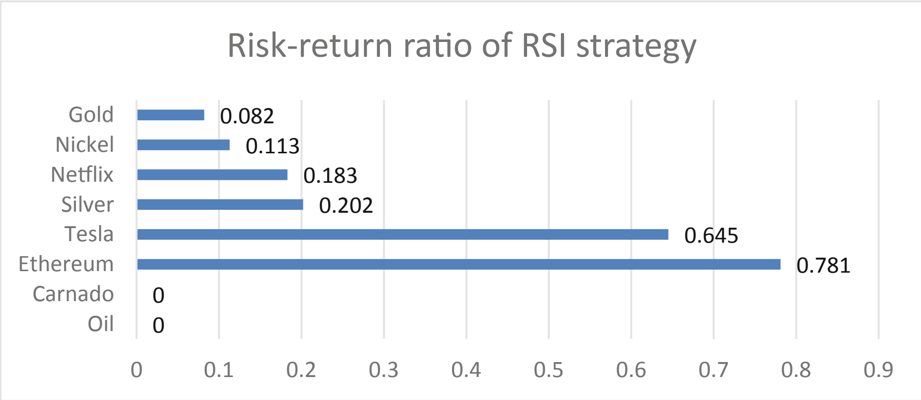

Fig. 15. Risk-return ratio of RSI strategy

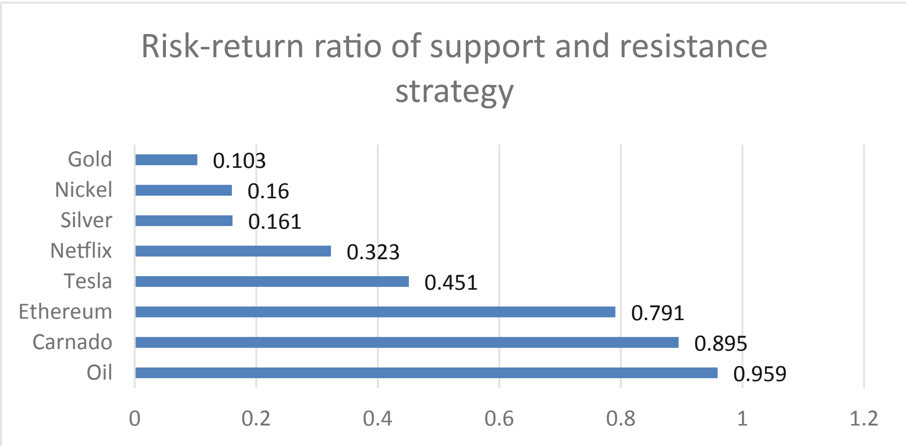

Fig. 16. Risk-return ratio of support and resistance strategy

5 Discussion

Developed software robo-advisor bot is prepared for different risk attitude investors who plan to meet their financial goals. Combining of different financial instruments in one investment portfolio can create unique combination of return and risk ratio, which is not coincide with such metrics of each asset alone. It creates opportunity for individuals to form such structure of their portfolio that is more correspondent to risk-return attitude of persons and their financial goals. The more financial assets of different types/from different industries choose an investor, the more diversified investment portfolio is. It reduces a non-systematic risk of the investors' portfolio. If investor get signal from bot that return of portfolio significant decrease/increase he/she can decide whether to buy/sell the asset(s) or not. It means that our bot is a type of self-service robo-advisor, because it provides information to an investor thereby assisting in the decision-making process.

The bot has also some limitations. Our analysis of risk-return ratio of investment portfolio is based on 252 previous days. It gives information to investor about some average values of return and risk of financial instruments. However, due to some shock events or unpredicted situations the risk-return criteria of investment portfolio can significantly changes. Consequences of such events will be the bias and larger confidence intervals of predicted return of investors. Risk attitude of investors and their goals can change over time and it will generate needs to rebalance portfolio structure by themselves. Our bot does not calculate margins of portfolio rebalancing which can decrease profitability of investment portfolio. It can be directions of our future research in this field.

6 Conclusions

The main types of robo-advisors are defined, including full service RAs (robo-managers that do not require any investor intervention and are fully automated), half-service RAs (a traditional or hybrid service that awaits confirmation of an investment transaction), self-service RAs providing investors freedom to cancel the robo-advisor recommendations. Among the existing RAs, the semi-service RA allows to take into account the investor personalized goals, because the investors can choose whether to implement the recommendations proposed by the algorithm or change them manually.

We developed the software module of an robo-advisor bot using Python Anaconda and Python Jupyter technology. Our developed software allows to calculate automatically the profitability and risk of financial instruments under investment strategies chosen for the investor goals.

The application of our software module reveals that some assets need more complex approach and assessment, taking into account several strategies simultaneously. It will help to make more quality and reliable forecasts. Each investor can choose different investment strategies, among which the most effective are "Buy-and-Hold", the strategy of the moving average, the strategy of the relative strength index RSI and the strategy of support and resistance.

For risk-averse investors all strategies according to the "risk-return" criterion for precious metals demonstrate the greatest efficiency. RSI (relative strength index), Buy-and-Hold strategies are also effective for Netflix shares. For risk-seeking investors all strategies include oil and cryptocurrencies. For risk-neutral investors Tesla stock is the most appropriate. This list of financial instruments is obviously not exhaustive and the investors preferences can include any other kinds of assets.

In the future, we plan to expand the functions of robo-advisor chat-bot. We are trying to develop of a full-fledged mobile application and website, to expand the range of strategies for providing more convenient and reliable consulting.

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