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# Portfolio Optimization Based on Fuzzy Investor Risk Classification Aligned with The Sri Framework

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**Abstract**

Choosing the right portfolio is challenging, especially for non-professional investors. In practice, investors are often classified into three risk profiles (conservative, balanced, dynamic), while investment products in the European Union are classified into seven categories using the Summary Risk Indicator (SRI). This mismatch may lead to investors with the same profile being recommended products with different risk levels. This paper proposes a methodology that aligns investor classification with the seven-level SRI scale. A fuzzy logic based investment questionnaire classifies investors into seven risk groups. For each group, a portfolio is constructed using Conditional Value at Risk optimization under undertakings for collective investment in transferable securities (UCITS) constraints. Empirical results

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based on Eurostoxx 50 data from 2020–2025 period show that the optimized portfolios achieved higher returns and lower downside risk than the benchmark. For example, the SRI 5 portfolio had an annual return of 16.12% compared to 11.3% for the benchmark.

**Keywords:** Undertakings for Collective Investment in Transferable Securities, Packaged Retail and Insurance-based Investment Products, The Markets in Financial Instruments Directive, fuzzy, risk profile, portfolio optimization

**JEL Classification:** G11, G18, G32, C61

# 1. Introduction

Achieving high returns is the most common requirement of most investors. However, not everyone realizes that high returns are also associated with high risk in the form of fluctuations in the value of financial assets. This market volatility is often attributed only to the negative side, but without volatility, high return assets could not exist. An ordinary non-professional investor has a difficult task in today's world if he wants to choose which investment instruments are the best for him. Without knowledge and experience in the field of financial markets, this is often impossible. It is precisely for these investors, who would often choose the wrong investment instruments, that several directives, regulations and regulations were created in the European Union. These instruments serve to protect investors and seek to reduce investor risk, for example by diversifying between several investment instruments. An advantage resulting from these regulations is also the need for greater awareness of the composition and risks of the investment asset offered.

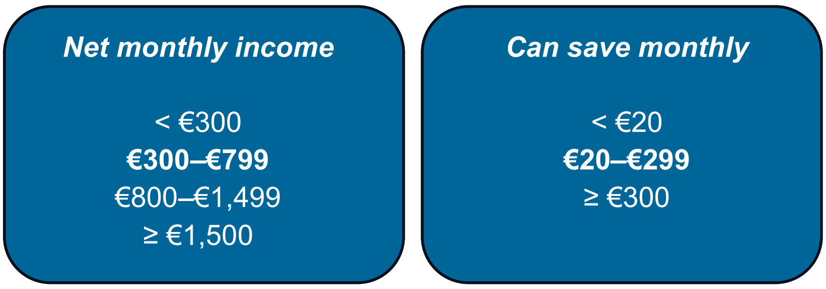
Another tool to help investors make the right choice is investment advisory, which is regulated by the European MiFID II (Markets in Financial Instrument Directive). This directive is applied when providing investment services across European investors and ensures a certain level of investor protection in the form of the need for market transparency or the obligation to test the suitability and adequacy of the investor. The second framework that affects the funds to which European investors can allocate their funds is UCITS (Undertakings for Collective Investment in Transferable Securities). Every fund offered to European investors has this designation at the end of its name, which speeds up the ability of investors to choose according to the European standard. This directive requires that every UCITS fund has a KIID (Key Investor Information Document), which contains standardized information about the fund, its costs and risks. UCITS also talks about restrictions on the composition of the fund and the maximum weights of individual securities. Together with these two directives, the PRIIPs regulation (Packaged Retail and Insurance-based Investment Products) has also been in use since 2018. As with UCITS, PRIIPs are also required to have a KID (Key

Information Document), which summarizes information about the product, for example about structured products or funds. This approach replaces the KIID document used until 2018. Together with these directives and restrictions, the European Commission is contributing to reducing investment risk and making funds more transparent, which can benefit investors who do not have the time or ability to examine each security in detail.

One of the changes that occurred with the application of PRIIPs was the adjustment of the risk assessment of funds. Since 2018, the methodology has been modified, which until now only considered the standard deviation of the fund and assigned a risk score from 1 to 7 based on the assigned interval. This methodology has proven to be insufficient and has been modified in PRIIPs, where several parameters such as skewness, kurtosis or VaR (Value at Risk) are added to the calculation. If we look at these guidelines, we will come across one of the problems whereas funds are rated on a scale from 1 to 7, but the depth of investor classification is not sufficient. The most common practice at the moment is to rate an investor based on an investment questionnaire into one of three risk groups (dynamic, balanced and conservative). If we consider seven categories of funds and only three risk profiles of investors, the question arises whether these categories are sufficient.

When looking at each of the three groups, there can be huge differences between investors at the upper and lower edge of a given group and their ability to bear risk is often diametrically different. At the moment, investment questionnaires that evaluate investor responses are built on the basis of static default answers that are unable to capture the real situation of the investor. A good example is a question about the investor's net income followed by a question about how much the investor is able to save per month. In this case, the question does not examine the percentage of capital that the investor is able to save compared to his net income, but only evaluates absolute values, which do not have a high informative value. We illustrate this shortcoming in Figure 1.

**Figure 1: Investment questionnaire**




Source: Authors' own elaboration

Figure 1 presents real questions and answers from one unnamed Slovak financial institution. Let us consider two investors who classified themselves into the highlighted groups in Figure 1. They could be students, part-time workers, but also people with permanent employment. If the first investor had an income of €300 and could save €250, he would be categorized in the same group as an investor who earns €750 and can save €20 per month. As can be seen in this example, this is a disproportion and it is not possible, in our opinion, to consider investors as belonging to the same risk category. We will solve this problem in this paper using Fuzzy logic, where we will approach each investor individually. The answers to the questions will be solved by filling in investor's own values without pre-filled options as it is done by now, which can often lead the investor to solutions that incorrectly determine a higher risk profile. Each question will be evaluated on a scale from 0 to 1, based on whether the investor has filled the required range with their answer. This way, we will be able to more accurately determine the investor's riskiness, as we will be able to look at each one individually and each questionnaire will thus become personalized. The output will be the aggregated average values of the answers, which will be interpreted as risk SRI (Summary risk indicator) values from 1 to 7. Since we are interested in covering the entire range of investors and focusing on all risk groups, when constructing portfolios we will consider not only stocks from the Eurostoxx 50 index, but also risk-free assets.

When constructing a portfolio, we will always strive to minimize risk, which will be solved using the CVaR (Conditional Value at Risk) method. The goal will be to create efficient stock portfolios (Markowitz, 1952) from the European Eurostoxx 50 index, which tracks the 50 largest and most liquid companies from the eurozone countries. In the first step, we will minimize the CVaR risk indicator. From this portfolio with the lowest possible risk, we will continually increase the returns and minimize the CVaR to it. From these portfolios, we will select representatives for SRI groups according to minimum risk. Those risk values represented by SRI that will not be available on the efficient frontier will be calculated through the ratio of stocks and bonds so that we are at the mean value of annualized volatility for the interval from which the SRI risk score is created. In the last step, we will compare the achieved results with the Eurostoxx 50 index itself and state the methodology used.

## 2. Literature review

Investing is an important topic for everyone, but not everyone has the ability to withstand pressure in difficult market situations. For this reason, several regulations and principles have been introduced that are recommended to be followed in order to reduce the number of investors who panic during problems in the financial markets and realize losses.

There are several regulations and directives through which the European Commission seeks to protect investors' portfolios across the Eurozone. One of the objectives of the European Commission, which affects all companies operating in the Eurozone, is that the European Commission has committed to a net-zero economy by 2050 and at the same time states that by 2030 it is necessary to reduce net greenhouse gas emissions by 55% compared to 1990 emissions (Grumann, Madaleno, Vieira, 2025). Of course, it should be noted that there are also discussions (Fröberg, Halling, 2024) and doubts (Yeoh, 2019) about whether MiFID II is really beneficial for investors.

Be that as it may, European directives and regulations need to be adapted as they determine the direction to which companies must adapt and thus affect business activities. From the perspective of non-professional investors, several regulations and regulations such as MiFID, UCITS or PRIIPS also arise and are also examined in several scientific articles. The basis for classifying an investor is an investment questionnaire, which forms the basis for assessing the investor's risk. In addition to the standard approach, with predefined answers, there are articles that examine the use of Fuzzy logic in investment questionnaires to determine risk (Zhang *et al.*, 2021). In this article, the authors do not consider regulations or directives for European investors and deal only with four evaluation criteria, which are age, education, gender and investment experience. From the perspective of MiFID, they do not meet the questions that must be asked of investors. In our work, we will expand this approach and create a questionnaire that has all the necessary questions to be used in practice to assess the investor's risk profile. After determining the risk, the authors used the Copula-GARCH model to model returns, which also differs from our principle of minimizing CVaR.

However, investment questionnaires have not yet addressed the classification of investors from the perspective of risk into 7 groups, as is the case with funds to which investors can allocate their funds. These 7 groups were calculated by the SRRI (Syntheric Risk and Reward Indicator) until 2018, and since 2018, SRI has been used, which considers multiple variables in the calculation. Our approach is to create an investment questionnaire using fuzzy logic, which is used in investing, for example, to assess the investment environment (Shevchenko, 2024) or to support investment decisions (Janková, Jana, Dostál, 2021). The difference between these risk indicators was also studied by authors from the investment bank BNP Paribas on their mutual funds. In this work, they concluded that their funds recorded a decrease in risk when switching from the SRRI metric to the SRI metric. They did not analyze the overall behavior of world indices, which we will address in this article. The conclusion of the study points to the higher availability of their funds for investors who would not have taken higher risks using the SRRI indicator until 2018 (Perchet, Herambourg, Carvalho, 2023).

In addition to the correct classification, high fees cannot be ignored, which often reduce investors' returns (Darpeix, 2024). Of these fees, the most well-known are entry and exit fees when executing a transaction, which immediately reduce the total investment volume when investing and when ending the investment (Baule, 2010). The second type is management fees, which investment companies often overestimate in order to achieve high profits (Wong, Li, 2024). The last group of fees used are performance fees (Broeders *et al.*, 2019), also called success fees. This group is often used in active portfolio management (Wang, 2022), but studies show that passive investing without intervention can be defeated by actively managed funds (Joshi, Dash, 2023). All investment funds offered to investors, whether passively or actively managed, must contain a key information document (Graf, Kling, 2020). This document also includes a summary risk indicator. In our work, we will not use SRI to only classify funds (portfolio structure), but we will use it also to classify investors into 7 groups so that each investor can immediately be assigned a portfolio with the appropriate level of risk.

Despite the growing literature on portfolio optimization and fuzzy logic in finance, previous studies have not integrated fuzzy-logic based investor questionnaires with the seven-level SRI classification used in European regulation. Few researches exists but it is not common in the studies to consider UCITS diversification constraints when constructing portfolios for different investor risk groups. This study addresses this gap by linking fuzzy investor classification with SRI risk categories and constructing representative portfolios under UCITS constraints.

# 3. Data and methodology

In this chapter, we will focus on the methods used, which will be applied in the construction of the investment questionnaire, its evaluation and subsequently in the construction of efficient portfolios.

## 3.1 Risk measurement

Risk (often referred to as uncertainty) is often an underestimated factor, but in fact it is just as important as return. Risk refers to fluctuations in the value of assets, which can be lower or higher than the investor expected. The most common negative impact of risk is that there is a chance of complete loss of the value of the capital invested. This risk can be reduced, for example, by diversification or by using risk measures such as standard deviation, VaR, CVaR or other indicators that tell us about the level of risk of the investment. In this article, we will use these risk measures. In portfolio management, the original author was the aforementioned Markowitz, who laid the foundations for portfolio risk in 1952. Markowitz expanded his original work in the late fifties and proposed a new risk measure (Markowitz, 1959). He called this measure of lower partial risk semi-variance or semi-dispersion. Lower partial risk measures include the VaR or CVaR, and investor interest in these risk measures has been growing steadily since the publication of the work. Lower partial risk measures have gained high popularity among investors mainly due to their suitability for use in the distribution of asset returns, which is asymmetric (Konno, Yamazaki, 1991). The semi-variance model can also be used in combination with multiple approaches, for example in portfolio construction using fuzzy logic (Huang, 2008). The risk represented by the standard deviation of returns, whether of a portfolio or of securities in general, represents a risk measure that expresses how much individual returns deviate from the average expected return in a given period. Markowitz used it in his work to measure portfolio risk, and until 2018 it was also used to interpret the riskiness of a fund using the SRRI indicator, which was based on the original UCITS directive intended for European investors.

The traditional method is also a framework for quantifying potential losses VaR or a coherent measure CVaR (Conditional Value at Risk). VaR has been a frequently used method in the past and has several applications in finance for risk management or asset allocation. It determines the maximum expected loss of a portfolio at a given confidence level over a certain period of time. However, this methodology is becoming obsolete as it faces limitations, such as its inability to take into account losses beyond a certain threshold. An extension of VaR is the CVaR method, which we will work with when constructing efficient portfolios. CVaR is a coherent quantile risk measure compared to VaR. Coherent measures for measuring risk were introduced in the work Coherent Measures of Risk (Artzner *et al.*, 1999). When investing, this measure helps to identify and manage risks that have the potential to cause significant losses. This method was developed and popularized by the authors R. T. Rockafellar and S. Uryasev in their works from the late 1990s and early 2000s. This work presents a new approach to optimizing a portfolio of financial instruments with the aim of reducing the risk of high losses. CVaR is used as a more consistent measure of risk than VaR (Rockafellar, Uryasev, 2000). CVaR focuses on the expected loss if the VaR threshold is exceeded. The reason for choosing the 95% CVaR level in this work, in addition to the most common use of this level, is that it represents the average of the worst 5% of values, which is computationally close to the 97.5% VaR calculation used in the SRI calculation explained in subsection 3.2.3. The choice of CVaR provides a more robust picture of risk and therefore its better incorporation into optimization models. The first work on CVaR had its expansion at the turn of this century. This article enriches the approach to optimization problems with CVaR constraints and can be used in particular to maximize expected returns under CVaR constraints (Krokhmal *et al*., 2003).

## 3.2 Regulations and directives

In this subsection, we will list the regulations, orders and directives from the European Commission that are used for funds provided to European investors. The most well-known are MiFID II, UCITS and PRIIPs.

### 3.2.1 MiFID II

MiFID and MiFID II are the European Union's regulatory directives for financial markets. Both directives were created by the European Commission, with the first MiFID being adopted in 2004 (Directive 2004/39/EC). This directive is effective in the European Union for all Member States that had to implement this directive in their national law. MiFID was introduced to regulate investment services and activities provided by investment firms, but it also applied to regulated markets. Individual Member States of the European Union had to establish in their national law that investment firms have the obligation to be authorized and subject to regulation if they provide investment services. One of the main reasons was the possibility of passporting, which represented the possibility of an investment firm to operate in member states of Eurozone. In terms of client categorization, the directive establishes retail client and professional client. MiFID also defines investment advisory, which is often used by retail clients. To provide such advice, the firm must have permission from the regulator and a license to provide investment services. A suitability test is also mandatory for investment advice. According to MiFID, this is the most important and most complicated test, which often appears under the term investment questionnaire with three areas. The first area is the client's investment objectives, where the investor's time horizon, preferred type of investment or risk tolerance are examined. The second group is the client's financial situation. The third category is the investor's experience and knowledge about investing. If the recommendation is not appropriate for the investor, it must not be provided. The second test is the Appropriateness Test, which is used for investment services without advice, also known as execution-only. The key differences between these tests are whether advice is provided or not. MiFID directive was replaced in 2018 by the newer MiFID II directive. The change came mainly due to several shortcomings that were also revealed during the financial crisis in 2008. New MiFID II directive was intended to ensure that securities trading would take place on regulated markets and that stricter rules would apply to OTC (Over the counter) trading. MiFID II also strengthened the suitability test, introduced the concept of target market, tightened the rules inducements, and required the provision of detailed information on costs & charges for each product offered.

### 3.2.2 UCITS

UCITS is a European directive that sets rules for retail funds that can be distributed across the European Union. The current directive in use is UCITS IV (2009/65/EC), which was amended in UCITS V (2014/91/EU). This directive sets out several restrictions that funds must comply with. The first restriction is the maximum weight of a single issuer, which UCITS sets at a maximum of 10%. The second restrictive condition is that issuers with a weight in the portfolio of more than 5% must together constitute a maximum of 40% of the portfolio. Together, these conditions stipulate that the minimum share of components in the portfolio will always be at least 17 securities. The liquidity of the fund in the form of the possibility of regular purchases and redemptions is also one of several conditions for a fund to be classified as a UCITS. It also stipulates the need to publish a KIID for each fund. This document contains short information about the fund, which must be understandable and comparable with other KIIDs. The obligation here is to explain the main risks, returns, costs of the fund and its strategy. In this two-page document, the risk is assessed using SRRI, which represents standardized tool for evaluating potential risk and return of an investment. The SRRI was introduced in order to simplify the information for investors in terms of potential riskiness and return of the specific fund and was valid until 2018 when it was replaced by SRI as part of PRIIPs. The higher the score of SRRI is, the higher the risk and return an investor can expect. SRRI is expressed through a single number that ranges from 1 to 7. The indicator is calculated based on the historical volatility of the fund, which is a measure of the fluctuations in the value of investments in the past. The volatility on which the SRRI is calculated is measured using the historical standard deviation of the fund's returns. A period of 5 years of historical returns is usually used to calculate the SRRI, if available. UCITS conditions can be written in the following formulation, where $w_j$ represents the weight of the asset $j$, and $j$ is from set of securities $NN$.

$$w_j \leq 0.10, \ \forall j \in NN \tag{1}$$

$$\textstyle\sum_{j \in NN: w_j > 0.05} w_j \leq 0.40, \ \forall j \in NN \tag{2}$$

Each score from 1 to 7 represents the final value behind the volatility intervals. These intervals have been made by European Securities and Markets Authority (European Securities and Markets Authority, 2015).

### 3.2.3 PRIIPs

PRIIPs is a European Union regulation effective from 1 January 2018. This regulation is used to protect retail investors in products that meet the following requirements: they are structured and packaged, have an investment component, and are complex to understand. These include, for example, structured deposits, structured bonds or UCITS funds for retail investors. PRIIPs came into force because investors often did not understand the investment assets in which they invested. For this reason, an information standard in the form of a KID document was introduced. This document requires that each product has the same: structure, expression of risk and view of performance scenarios and costs of investing in the product. Each KID must contain a product description and an expression of the product's risk using an SRI score, which replaces the original SRRI from UCITS. SRI is no longer calculated solely on the basis of the standard deviation of the fund's price, but metrics such as MRM (Market risk meassure) and CRM (Credit risk meassure) are considered. MRM represents a measurement of the product's market risk using the annualized volatility VEV. This value uses the VaR value, kurtosis, skewness, and also the fund's standard deviation. Together, this approach creates a more robust risk classification process than when only the fund's standard deviation was originally considered. CRM is used to assess the credit risk of the issuer or counterparty. It measures the probability of failure to repay investors, also known as default risk. CRM takes into account the issuer's credit rating, the probability of default, but also the company's financial strength and stability. CRM is calculated based on ratings from rating agencies such as S&P or Moody's and Fitch. Common UCITS funds have low risk (usually CRM 1). For this reason, we can only use MRM when considering the calculation of SRI, since the value of MRM will always be greater than or equal to CRM and therefore SRI will be equal to the value of MRM. A comparison of the final table for calculating SRI and SRRI is shown in table 1.

**Table 1: SRI vs SRRI approach**

| SRI (MRM) | Volatility intervals (VEV, in %) | | | |
|---|---|---|---|---|
| | Equal or more | Less | SRRI | Volatility (σ, in %) |
| **1** | 0 | 0.5 | 1 | 0–0.5 |
| **2** | 0.5 | 5 | 2 | 0.5–2 |
| **3** | 5 | 12 | 3 | 2–5 |
| **4** | 12 | 20 | 4 | 5–10 |
| **5** | 20 | 30 | 5 | 10–15 |
| **6** | 30 | 80 | 6 | 15–25 |
| **7** | 80 | | 7 | > 25 |

Source: Authors' own elaboration

The VEV value is calculated according to the following formula:

$$VEV = \frac{\sqrt{(3{,}842 - 2 \times VaR_{SPACERETURN}) - 1{,}96}}{\sqrt{T}} \tag{3}$$

where $VaR_{SPACERETURN}$ is represented by:

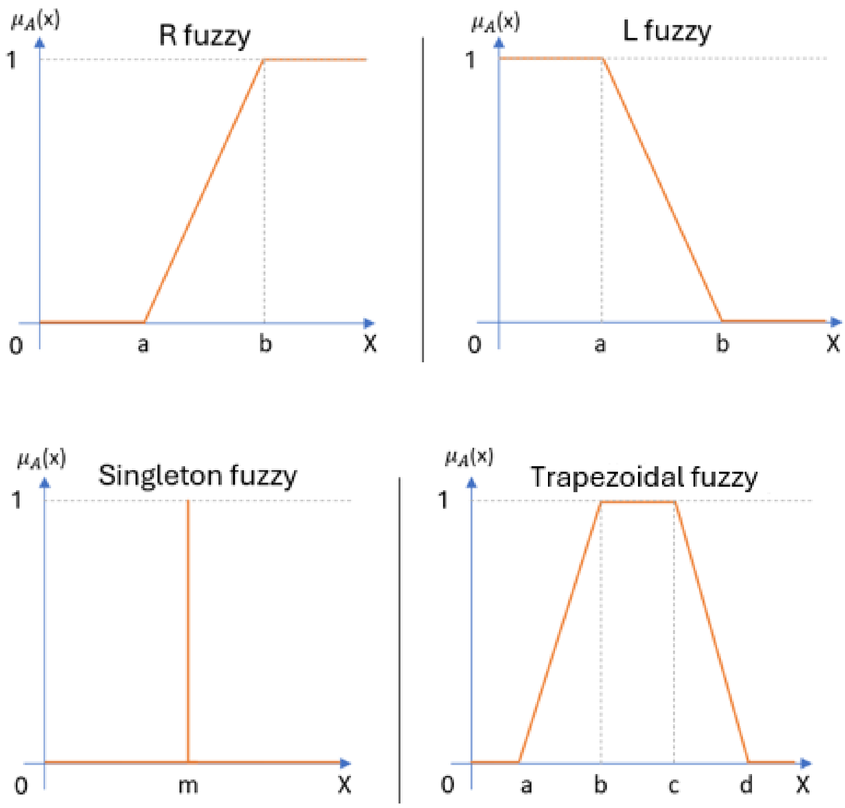
$$VaR_{SPACERETURN} = \sigma\sqrt{N} \times \left(-1.96 + 0.474\frac{\mu_1}{\sqrt{N}} - 0.0687\frac{\mu_2}{\sqrt{N}} + 0.146\frac{{\mu_1}^2}{\sqrt{N}}\right) - 0.5\,\sigma^2 N \tag{4}$$

$N$ represents number of trading periods in the recommended holding period, $\sigma$ represents volatility, $T$ is recommended period for holding the asset in years, $\mu_1$ stands for skewness and $\mu_2$ represents the excess kurtosis – measured from the distribution of return.

## 3.3 Fuzzy logic

When creating an investment questionnaire, it was necessary to consider a way to evaluate the investor's answers other than with static predefined answers. One way to approach this issue is using Fuzzy logic, where the answers will always represent numerical values provided by the investor. These values are then transformed as affiliations in Fuzzy sets from the interval from 0 to 1 based on meeting the criteria of the given question. In this questionnaire, we will use several types of Fuzzy sets such as: Fuzzy L, Fuzzy R, Fuzzy singleton or Trapezoidal fuzzy set (Mohan, 2017). Each of the Fuzzy sets has properties such as support, core and height as shown at Figure 2 (Zadeh, 1965).

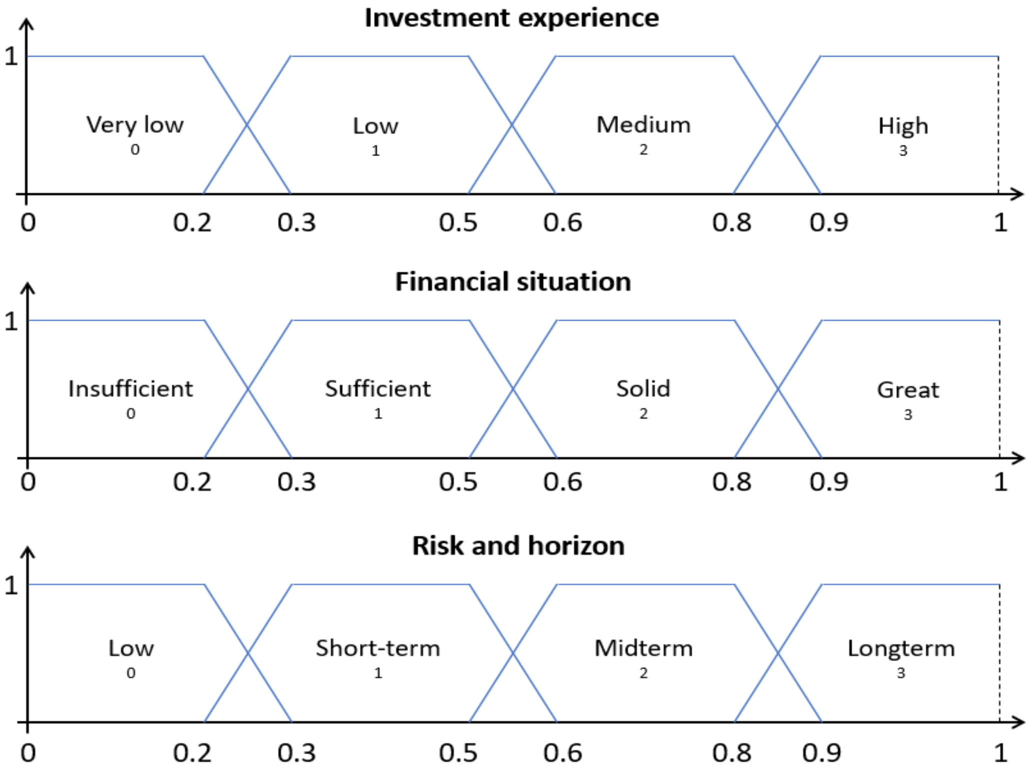
**Figure 2: Used Fuzzy sets**




Source: Authors' own elaboration

In the investment questionnaire, we consider several groups of questions focused on: the investor's financial situation, investment goals and preferences, ability to bear risk and losses and knowledge and experience. The values of the answered questions are aggregated and averaged by groups of questions, which gives the average value of the affiliation of each group. Since the questionnaire requires answers as numerical values, we will only use the first three groups in the SRI calculation, since knowledge and experience are focused on choosing from several investment assets, which cannot be interpreted numerically. From the three groups, we will create linguistic variables that will interpret the inputs to the matrix for evaluating the investor's SRI score. The linguistic variables, whose values are the average of the affiliations, are shown in Figure 3.

**Figure 3: Linguistic variables**




Source: Authors' own elaboration

Based on figure 3, we can construct a matrix to evaluate the resulting SRI. This matrix has 64 different possible combinations (power of three groups with four options) that guarantee coverage of the risk score from 1 to 7. We can then construct the resulting SRI matrix, which is shown in table 2. The lowest possible SRI value: 1, is created from answers with the value (0, 0, 0) for all three groups to the highest possible SRI value: 7 with the values (3, 3, 3).

**Table 2: SRI matrix**

| INPUT | SRI | INPUT | SRI | INPUT | SRI | INPUT | SRI |
|---|---|---|---|---|---|---|---|
| 0, 0, 0 | 1 | 1, 0, 0 | 1 | 2, 0, 0 | 2 | 3, 0, 0 | 3 |
| 0, 0, 1 | 1 | 1, 0, 1 | 2 | 2, 0, 1 | 2 | 3, 0, 1 | 3 |
| 0, 0, 2 | 2 | 1, 0, 2 | 2 | 2, 0, 2 | 3 | 3, 0, 2 | 4 |
| 0, 0, 3 | 3 | 1, 0, 3 | 3 | 2, 0, 3 | 4 | 3, 0, 3 | 4 |
| 0, 1, 0 | 1 | 1, 1, 0 | 2 | 2, 1, 0 | 2 | 3, 1, 0 | 3 |
| 0, 1, 1 | 2 | 1, 1, 1 | 3 | 2, 1, 1 | 3 | 3, 1, 1 | 4 |
| 0, 1, 2 | 2 | 1, 1, 2 | 3 | 2, 1, 2 | 4 | 3, 1, 2 | 5 |
| 0, 1, 3 | 3 | 1, 1, 3 | 4 | 2, 1, 3 | 5 | 3, 1, 3 | 6 |
| 0, 2, 0 | 2 | 1, 2, 0 | 2 | 2, 2, 0 | 3 | 3, 2, 0 | 4 |
| 0, 2, 1 | 2 | 1, 2, 1 | 3 | 2, 2, 1 | 4 | 3, 2, 1 | 5 |
| 0, 2, 2 | 3 | 1, 2, 2 | 4 | 2, 2, 2 | 5 | 3, 2, 2 | 6 |
| 0, 2, 3 | 4 | 1, 2, 3 | 5 | 2, 2, 3 | 6 | 3, 2, 3 | 6 |
| 0, 3, 0 | 3 | 1, 3, 0 | 3 | 2, 3, 0 | 4 | 3, 3, 0 | 4 |
| 0, 3, 1 | 3 | 1, 3, 1 | 4 | 2, 3, 1 | 5 | 3, 3, 1 | 6 |
| 0, 3, 2 | 4 | 1, 3, 2 | 5 | 2, 3, 2 | 6 | 3, 3, 2 | 6 |
| 0, 3, 3 | 4 | 1, 3, 3 | 6 | 2, 3, 3 | 6 | 3, 3, 3 | 7 |

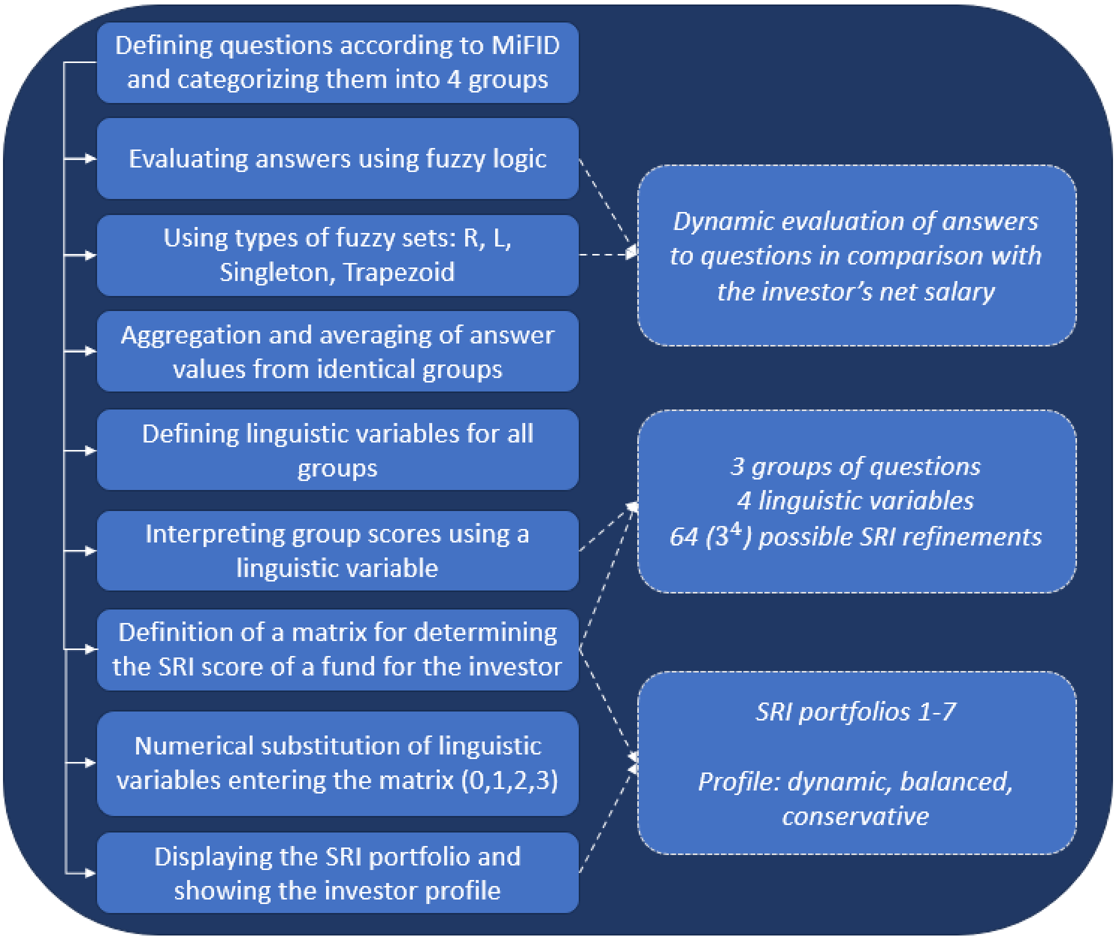
Source: Authors' own elaboration

The SRI matrix from Table 2 is a methodological proposal built for the purpose of this study. European regulation does not define a standardized rule for mapping questionnaire results to final SRI categories for investor classification. The only fixed boundary to the SRI level are the lowest possible combination of risk factors that corresponds to the lowest risk score and the highest combination corresponds to the highest score. The matrix is constructed so that the combination (0,0,0) corresponds to SRI 1 and the combination (3,3,3) corresponds to SRI 7. All other possible combinations represent a gradual increase in risk according to the intensity of the three evaluated dimensions by fuzzy logic. The specific assignments within the matrix represent a reasonable progression of risk levels and serve as a recommendation for linking fuzzy investor classification with the seven-level SRI framework. With the original approach, where there were only three risk groups of investors and seven fund groups, we could choose funds from one of many risk groups which might not fit for the investors' real risk profile. Moreover, in the traditional three-profile model may, funds may overlap and be assigned to two categories of investors because the SRI ranges of categories are not clearly defined.

## 3.4 Assessing model

So far, we have presented fuzzy logic, which will be used in the work to implement an investment questionnaire, which will determine one of seven risk groups that will be assigned to the investor based on his answers in the investment questionnaire. The general diagram of calculating the SRI value of an investor is shown in Figure 4.

**Figure 4: Universal approach to assessing investor based on SRI**




Source: Authors' own elaboration

After receiving the risk score, we can determine, based on the definition of SRI from Chapter 3.3, in which volatility interval the investor's portfolio must be in order to meet the standard of the European directive. When constructing the model, we will consider two types of securities. The first type is a risk-free security. In theoretical portfolio models, the yield of long-term government bonds such as German ten-year government bond is often used as an approximation of risk-free asset. However, such instruments typically require high nominal investment amounts and are therefore not directly accessible to most retail investors. For this reason, the proposed model does not use these bonds as the risk-free asset. Instead, this component is represented by instruments that are realistically available to retail investors, such as money market funds or the funds that tracks the overnight euro swap rate set by the European Central Bank. These instruments serve as a practical substitute for the theoretical risk-free asset used in classical portfolio theory. In the empirical implementation of the model, the risk-free allocation is therefore represented by money market instruments rather than long-term government bonds. The second asset type are equities of companies selected from a predetermined index Eurostox 50. All companies that are currently listed there and have at least a five-year history of listing on the stock exchange will be selected from this index. Seven portfolios will always be created – one for each SRI risk group, while the portfolios will take into account the riskiness of each investor.

The first step is to calculate the portfolios that are on the efficient frontier. This frontier is formed by purely equity portfolios, with the horizontal axis representing CVaR as a representative of risk and the vertical axis representing the annual return of the portfolio. Individual portfolios will have different compositions in terms of stock weights, but also portfolio composition, while the exact number of shares in the portfolio is not predetermined, so the portfolios will have different numbers of shares. The objective function minimizes the CVaR of the portfolio. The calculation includes the loss threshold and the average "excess loss", which makes the CVaR the expected loss in the worst specified scenarios according to the indicator $\alpha$. We write the minimization objective function as follows:

$$\min_{w,z,VaR} VaR + \frac{1}{\alpha T} \sum_{t=1}^{T} z_t \tag{5}$$

Here, we define constraints and variable definitions such as the auxiliary variable $z_t$, which represents scenario constraints:

$$\hat{z_t} + \sum_{j=1}^{n} w_j r_{t,j} + VaR \geq 0, \ \forall t = 1, \ldots, n_T \tag{6}$$

The weights must be non-negative (long position) – no shorting:

$$w_j \geq 0, \ \forall j \in NN \tag{7}$$

Only negative deviations (losses) enter CVaR:

$$z_t \geq -\left(E_p{}^{(W)} + VaR\right);\ z_t \geq 0,\ \forall t = 1, \dots, n_T \tag{8}$$

The weights must be fully invested. The total sum of the weights must equal one:

$$\sum_{j=1}^{n} w_j = 1 \tag{9}$$

Optional restriction on the minimum expected return of the portfolio, which subsequently generates efficient frontiers.

$$\sum_{j=1}^{n} w_j E_j \geq R_{min} \tag{10}$$

We write the weekly portfolio return as:

$$E_p{}^{(W)} = r_j w_j \tag{11}$$

Whereby we calculate the annual portfolio return as:

$$E_p{}^{(Y)} = \left(1 + E_p\right)^{52} - 1 \tag{12}$$

where the variables and parameters are as follows: $E_p{}^{(W)}$ is weekly expected return of portfolio, $E_p{}^{(Y)}$ is yearly expected return of portfolio, $w_j$ represents the decisive variable – the weight in asset $j$, where $j \in NN = \{1, ..., nn\}$, $VaR$ is the value of the Value at Risk limit (loss threshold), $z_t$ is an auxiliary variable for CVaR, while exceeding the loss limit in the period $t$ represents $z_t > 0$, where $t \in T = \{1, ..., n_T\}$, $T$ represents the set of all weekly periods $T = \{1, ..., n_T\}$, $N$ is the set of all investment assets $NN = \{1, ..., n\}$, $n_T$ represents the number of periods in weeks, $r_{t,j}$ is the actual return on the asset $j \in NN$ where $t \in T$, $\alpha$ is the confidence level for CVaR from the interval (0,1), in our case the level is 0.05, $r_j$ is the expected weekly return of the asset $j$, $R_{min}$ is the required minimum expected return.

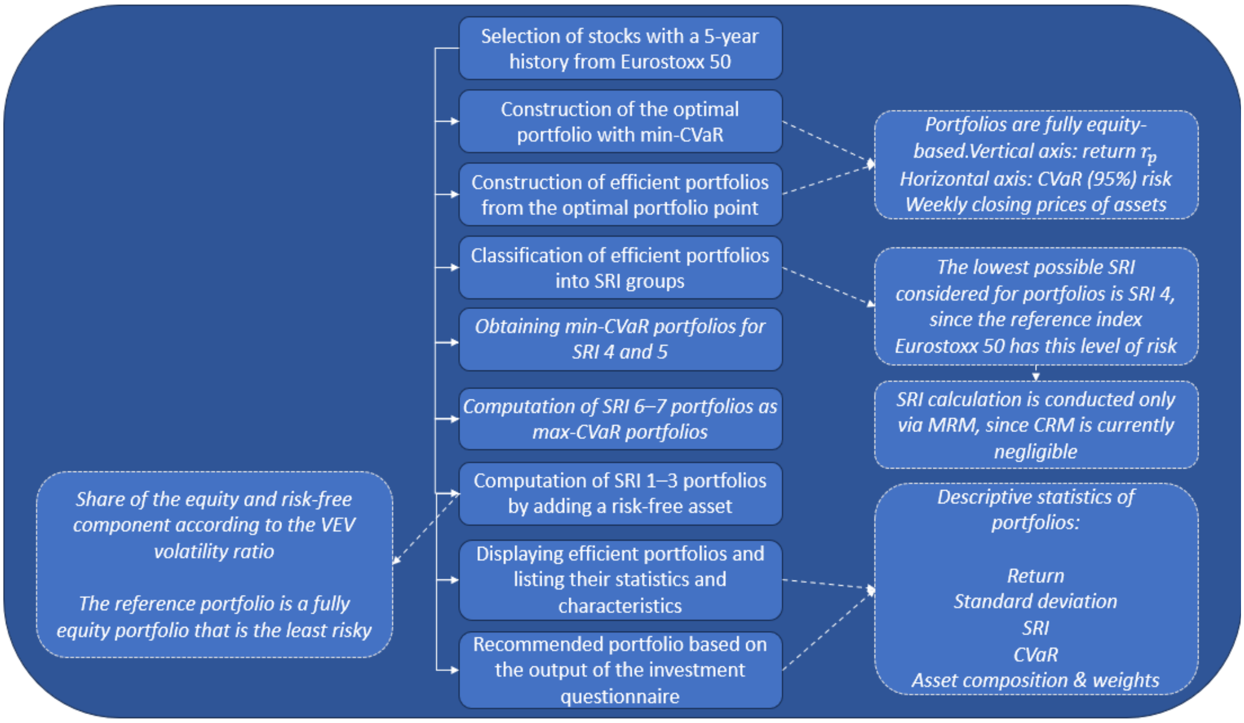
After calculating the efficient frontier, it is necessary to sort the portfolios by SRI values. From these portfolios, we then select a portfolio based on the minimization of the CVaR value, which gives us one equity portfolio for each of the available SRI groups. The remaining portfolios with missing SRI are added as a share of risk to the least risky portfolio from the SRI perspective and we apply the appropriate percentage ratio between the fully equity component of this reference portfolio and the bond component based on the VEV value. The calculation of the equity and bond components is shown mathematically:

$$EC = \frac{VEVx}{VEVy} \tag{13}$$

$$BC = 1 - EC \tag{14}$$

where *EC* represents the equity component of the portfolio, *VEVx* represents the median value defined in PRIIPs, *VEVy* is value of VEV a fully equity portfolio with the lowest possible SRI, *BC* is the bond component of the portfolio. In general, unless we have a precise VEV value for the portfolio and know which SRI group it is in, we will use the mean value from the intervals in Table 1. The model construction is shown in Figure 5.

**Figure 5: Investing model**




Source: Authors' own elaboration

# 4. Empirical results

In this chapter, we will focus on the construction of an investment questionnaire, its valuation and the subsequent creation of efficient portfolios using the Python software program. The approach used for risk classification is SRI, which has replaced the original SRRI method since 2018. The new method of risk valuation does not depend only on the standard deviation and is often less restrictive, which reduces the original value of the SRRI score of the fund. In the first step, we analyzed three stock indices from the Eurozone: Eurostoxx 50, the German DAX index and the FTSE 100. As can be seen in Figure 8, the SRI approach (3) is less restrictive and thus allows a larger group of investors to allocate their funds to equity funds, which supports their growth in value. The new calculation method often allows investors who did not achieve a sufficient risk profile to invest in riskier underlying assets whose scores have been reduced, even if it is the same asset. For both risk indicators, the maximum value that can be obtained is 7 and the lowest risk score for both indicators is 1.

**Figure 6: Eurozone stock indices**

| Period (5 years) | STOXX50_ SRRI | STOXX50_ SRRI(MRM) | DAX40_ SRRI | DAX40_ SRRI(MRM) | FTSE100_ SRRI | FTSE100_ SRRI(MRM) |
|---|---|---|---|---|---|---|
| **2012-01-01 – 2016-12-31** | 6 | 5 | 6 | 6 | 5 | 4 |
| **2013-01-01 – 2017-12-31** | 6 | 5 | 6 | 6 | 5 | 4 |
| **2014-01-01 – 2018-12-31** | 6 | 5 | 6 | 5 | 5 | 4 |
| **2015-01-01 – 2019-12-31** | 6 | 5 | 6 | 5 | 5 | 4 |
| **2016-01-01 – 2020-12-31** | 6 | 6 | 6 | 5 | 6 | 5 |
| **2017-01-01 – 2021-12-31** | 6 | 6 | 6 | 5 | 6 | 5 |
| **2018-01-01 – 2022-12-31** | 6 | 6 | 6 | 5 | 6 | 5 |
| **2019-01-01 – 2023-12-31** | 6 | 6 | 6 | 6 | 6 | 5 |
| **2020-01-01 – 2024-12-31** | 6 | 6 | 6 | 6 | 6 | 5 |
| **2021-01-01 – 2025-12-31** | 6 | 6 | 6 | 6 | 6 | 5 |

Source: Authors' own elaboration

We obtained the values in Figure 6 by moving a five-year window forward by one year from 2012 to 2025. The red color shows the decrease in the SRI value over the same five-year window compared to the original SRRI value for the same period. The longer time span from 2012 to 2025 is used only for the purpose of illustrating the difference between the SRRI and SRI methodologies through rolling five-year windows. The portfolio optimization analysis itself is performed on the most recent five-year period (2020–2025), which corresponds to the standard data horizon commonly used for risk assessment in the PRIIPs framework.

## 4.1 Risk profile classification

The first step in assessing the risk of an investor is classification into a risk group. The current approach, which includes only 3 risk groups, is not robust enough and for this reason we have proposed a new alternative solution for risk classification. The method that solves this problem is Fuzzy logic, where we always set the interval of affiliation from 0 to 1. Let us list some of the questions used in the investment questionnaire. The first question is income, which is classified using the Fuzzy R set. We defined the interval where the carrier of the Fuzzy set begins at the minimum net wage for the previous year and we set the beginning of the core at the point of the average net monthly salary for the last year. In the case of data from the Statistical Office of the Slovak Republic, the minimum net wage is €615 and the average wage in 2024 is €1,130. (Statistical Office of the Slovak Republic, 2024). The following question follows again from Figure 1 and is focused on the ability to save funds monthly. If the investor can save more than 10% of his net income then he will get the value of affiliation 1 for this given question.

Other questions for the first group which are focused on financial status of the investor: **current financial reseve**, which should represent at least six times the net income in order for the question to be assigned the relevance of answer 1, **investor's asset value**, which if it is greater than 24 times the net monthly salary, we assign the value 1 and the last question of the first group is **monthly mortgage payment**, where we use the Fuzzy L set, and the value here must not exceed 43% of the investor's net salary, otherwise we assign the value 0. we determined it using the Fuzzy R set. **The second group** is **investment goals and preferences**, where we examine the main investment goal, the planned investment horizon and examine what percentage of the monthly balance after deducting expenses the investor is willing to invest. **The third group** is the **ability to bear risk and losses**, where we examine how stable the investor's income is, how the investor would react to a decrease in investment during periods of downturn, what is the largest loss from the invested money that would not pose existential problems for the investor and what is the investor's age.

All these questions form a personalized questionnaire for each investor, as the answers are approached individually based on the data that investors enter as input values. The advantage of this questionnaire is that it better reflects the client's life situation, as it takes into account the connection between the current financial situation and the investor's possibilities. The parameters of the fuzzy membership functions used in the investment questionnaire are calibrated primarily for a typical Slovak retail investor. The threshold values were determined using publicly available macroeconomic statistics and commonly used financial planning recommendations. In particular, income-related thresholds are based on data from the Statistical Office of the Slovak Republic for the year 2024. The minimum net monthly wage (approximately €615) and the average net monthly wage (approximately €1,130) are used as reference points when defining the membership functions for the income variable.

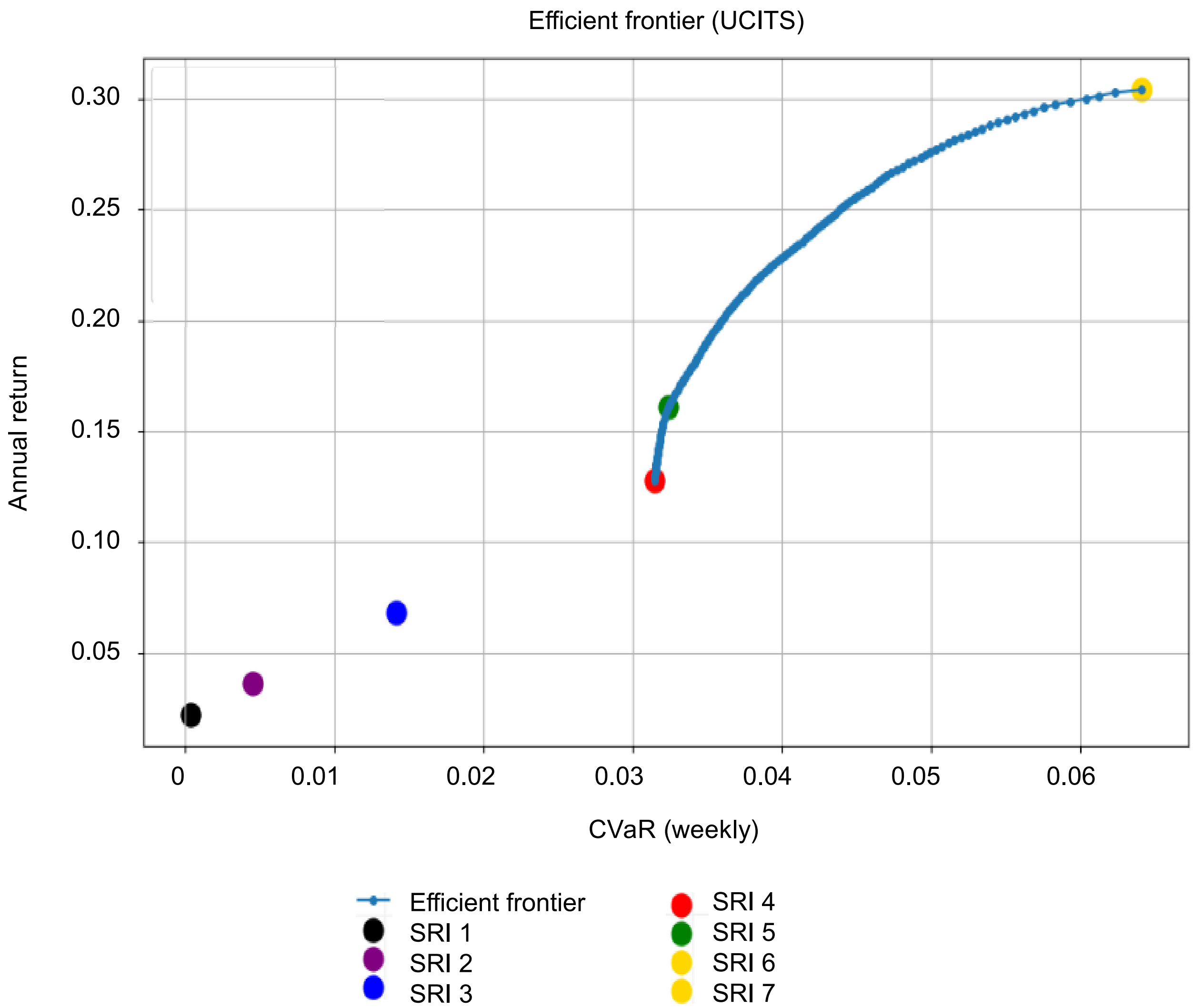
These values represent lower and typical income levels in the Slovak economy and therefore provide a reasonable calibration for the questionnaire. Other parameters of the questionnaire follow standard financial planning recommendations. For example, the recommended financial reserve of six months of income is widely used as a benchmark for household financial stability. The thresholds used for debt obligations are based on common debt-to-income guidelines, where values around 43% are typically considered the maximum sustainable level of indebtedness. Similarly, the five-year investment horizon reflects the commonly recommended minimum investment period used by many financial institutions for equity investments. Although the parameters are calibrated using Slovak economic conditions, the proposed framework is flexible and can be easily adapted to other countries by adjusting the threshold values according to national income statistics and financial planning standards.

## 4.2 Construction of SRI portfolios

After obtaining information about the investor's risk score using Fuzzy logic, we approach the construction of a portfolio that will meet the investor's risk profile. The first step is to load data of all companies from the Eurostoxx 50 index. The Eurostoxx 50 index was selected because it represents the largest and most liquid blue-chip companies in the eurozone. At the same time, it is one of the most widely used benchmarks for European equity markets and therefore provides a representative and realistic set of investable assets for portfolio construction. The index is used as a representative investment universe for eurozone equity markets, but the framework itself is not tied to a specific index or a group of assets. Our methodology can be applied to any investment universe. This data represents weekly closing values of equities from 16.11.2020 to 16.11.2025. In the Python code, we define the model and its constraints based on UCITS, which will guarantee that the portfolio composition will always consist of at least 17 stocks. The bond component will be added for portfolios with a lower SRI than can be achieved from the efficient frontier. After loading prices and defining functions, we generate the first portfolio with the lowest CVaR, which in this case was SRI 4. After acquiring the portfolio with the lowest CVaR, we increase the returns by 0.01% per year and minimize the risk in the form of CVaR to this return value. In this way, we obtain an efficient portfolio frontier, and the lower the increase in return, the more granular and precise the efficient frontier will be. The last portfolio generated would be a single-component portfolio representing the most profitable stock without UCITS conditions. Considering these constraints, the last portfolio with the highest risk will be the portfolio that still meets the constraints and it is not possible to find a portfolio that would have at least 17 components, a maximum asset weight of 10% and components with more than 5% weighting to make up at most 40% of the portfolio.

Portfolios with SRI values of 4 and 5 were generated on the efficient frontier. For both selected portfolios, the representative of the group will be the portfolio from the SRI group that has the lowest SRI value. Portfolios with a higher SRI than those available on the efficient frontier (in our case 6 and 7) will represent the portfolio with the highest possible CVaR from the efficient frontier. For portfolios that have a lower SRI value than is available on the efficient frontier, we vary the share of the equity and bond components according to the ratio of the mean annualized volatility of the sought portfolio and the portfolio with the lowest SRI (in our case SRI 4). We show these portfolios and the efficient frontier with use of CVaR 95, with rate of return of risk-free asset of 0.04% weekly (~ 2% yearly) in Figure 7.

**Figure 7: Efficient frontier with min-CVaR95 SRI portfolios**




Source: Authors' own elaboration

The optimization is performed on the selected set of assets, in this case the equities from the Eurostoxx 50 index. As a result, not all SRI levels can be obtained directly from the efficient frontier that follows UCITS constraints. The lowest-risk portfolio that can be constructed using only equities corresponds to the SRI 4 category. Portfolios with SRI levels 1–3 are constructed by combining this optimized SRI 4 portfolio with a risk-free component represented by money market instruments. This procedure follows the standard portfolio theory approach, where lower-risk portfolios are obtained as linear combinations of a risky portfolio and a risk-free asset. This approach allows the portfolio volatility to be reduced while preserving the optimized structure of the equity allocation. On the opposite side of the efficient frontier, the riskiest portfolio obtained from the optimization represents the highest feasible risk level under the UCITS diversification constraints. Since no portfolio with higher volatility can be constructed under these conditions, this portfolio is assigned to both SRI 6 and SRI 7 categories. If we look at Figure 7, we find two full-stock portfolios for the available SRI groups. The Eurostoxx 50 index is used as a benchmark in the empirical analysis because it represents the underlying investment universe from which the portfolios are constructed. Comparing the optimized portfolios with the benchmark index allows us to evaluate whether the optimization procedure improves the risk-return characteristics relative to the passive market portfolio. As shown in Table 3, these portfolios (SRI 4 and SRI 5) outperform the benchmark index Eurostoxx 50 in returns while having lower risk.

**Table 3: Portfolio statistics of min-CVaR95 optimized SRI portfolios**

| Metric | SRI 1 | SRI 2 | SRI 3 | SRI 4 | SRI 5 | SRI 6, 7 | Eurostoxx 50 index |
|---|---|---|---|---|---|---|---|
| **Annual return** | 2.23% | 3.61% | 6.68% | 12.79% | 16.12% | 30.40% | 11.30% |
| **CVaR 95** | 0.0004 | 0.0046 | 0.0141 | 0.0315 | 0.0324 | 0.0641 | 0.0514 |
| **VaR 95** | 0.0003 | 0.0035 | 0.0108 | 0.0237 | 0.0225 | 0.0338 | 0.0352 |
| **Standard deviation** | 0.0015 | 0.0171 | 0.0523 | 0.1164 | 0.1191 | 0.1915 | 0.1605 |
| **Sharpe ratio** | 0.8768 | 0.8826 | 0.8960 | 0.9227 | 1.177 | 1.478 | 0.5785 |
| **VEV** | 1.29 | 3.65 | 9.07 | 18.82 | 20.04 | 29.78 (SRI 5) | 31.49 (SRI 6) |
| **Number of stocks** | 18 | 18 | 18 | 18 | 17 | 17 | 48 |
| **Stocks** | 1.34% | 14.73% | 45.51% | 100% | 100% | 100% | 100% |
| **Money Market** | 98.66% | 85.27% | 54.49% | 0% | 0% | 0% | 0% |

Source: Authors' own elaboration

Portfolios with SRI 1–3 are created as combinations of the optimized lowest risk (based on SRI) full stock portfolio, which is SRI 4 and a risk-free asset, while SRI 6 and SRI 7 correspond to the highest-risk portfolio available on the efficient frontier under UCITS constraints. Since the method for portfolio construction in investment companies differs, we approximate the traditional three-profile classification by aggregating the SRI-based portfolios. With the new methodology the Conservative investor could be represented by average of SRI 1–3 portfolios. Balanced investor as the average of SRI 3–5 portfolios. Dynamic investor as the average of SRI 5–7 portfolios. This approach allows us to create portfolios for comparison purposes while maintaining consistency with the SRI-based framework. To verify the robustness of the model, portfolio optimization was also evaluated using alternative CVaR confidence levels. In addition to the baseline specification using CVaR 95, the optimization was repeated using CVaR 99 and CVaR 90. The use of CVaR at the 95% confidence level is motivated by the fact that it represents the average of the worst 5% outcomes, which is conceptually close to the 97.5% Value at Risk used in the PRIIPs regulation for the calculation of the SRI indicator. The CVaR 99 option is shown in Table 4.

**Table 4: Portfolio statistics of min-CVaR99 optimized SRI portfolios**

| Metric | SRI 1 | SRI 2 | SRI 3 | SRI 4 | SRI 5 | SRI 6, 7 | Eurostoxx 50 index |
|---|---|---|---|---|---|---|---|
| Annual return | 2.20% | 3.15% | 5.36% | 9.25% | 13.52% | 29.84% | 11.3% |
| CVaR 99 | 0.0005 | 0.0058 | 0.0159 | 0.0430 | 0.0455 | 0.1142 | 0.0836 |
| VaR 99 | 0.0004 | 0.0051 | 0.0159 | 0.0342 | 0.0340 | 0.0712 | 0.0538 |
| Standard deviation | 0.0016 | 0.0186 | 0.0577 | 0.1238 | 0.1265 | 0.1924 | 0.1605 |
| Sharpe ratio | 0.5569 | 0.56 | 0.5654 | 0.577 | 0.9024 | 1.472 | 0.5785 |
| VEV | 1.29 | 3.65 | 9.07 | 18.28 | 20.00 | 29.84 (SRI 5) | 31.49 (SRI 6) |
| Number of stocks | 17 | 17 | 17 | 17 | 19 | 17 | 48 |
| Stocks | 1.37% | 15.05% | 46.50% | 100% | 100% | 100% | 100% |
| Money Market | 98.63% | 84.95% | 53.50% | 0% | 0% | 0% | 0% |

Source: Authors' own elaboration

When optimization is performed using CVaR 99, the model becomes more conservative, as the risk measure focuses on more extreme losses. As a result, the expected portfolio return decreases while the reported CVaR value increases, and the portfolio composition changes slightly. In Table 5 the SRI 6 can also be seen as the maximum value of VEV is 30.23 which is from the SRI 6 interval.

**Table 5: Portfolio statistics of min-CVaR90 optimized SRI portfolios**

| Metric | SRI 1 | SRI 2 | SRI 3 | SRI 4 | SRI 5 | SRI 6, 7 | Eurostoxx 50 index |
|---|---|---|---|---|---|---|---|
| Annual return | 2.25% | 3.70% | 7.11% | 13.58% | 15.60% | 30.49% | 11.3% |
| CVaR 90 | 0.0003 | 0.0035 | 0.0110 | 0.0252 | 0.0254 | 0.0483 | 0.0401 |
| VaR 90 | 0.0002 | 0.0022 | 0.0067 | 0.0150 | 0.0157 | 0.0274 | 0.0225 |
| Standard deviation | 0.0015 | 0.0166 | 0.0515 | 0.1143 | 0.1170 | 0.1963 | 0.1605 |
| Sharpe ratio | 0.9512 | 0.9578 | 0.9733 | 1.004 | 1.1532 | 1.446 | 0.5785 |
| VEV | 1.30 | 3.66 | 9.85 | 18.93 | 20.09 | 30.23 (SRI 6) | 31.49 (SRI 6) |
| Number of stocks | 19 | 19 | 19 | 19 | 19 | 17 | 48 |
| Stocks | 1.34% | 14.73% | 45.51% | 100% | 100% | 100% | 100% |
| Money Market | 98.66% | 85.27% | 54.49% | 0% | 0% | 0% | 0% |

Source: Authors' own elaboration

When using CVaR 90, the model focuses on less extreme losses. This results in slightly higher portfolio returns and lower CVaR values, while the portfolio composition changes only marginally (one additional stock appears in the SRI 5 portfolio). Overall, the results indicate that the portfolio structure remains relatively stable across different confidence levels. The results show that the UCITS-constrained portfolios outperform the Eurostoxx 50 benchmark index over the last five years from 16 November 2020 to 16 November 2025. Since Eurostoxx 50 has the SRI 6 as can be seen on figure 6, the SRI 6 UCITS-constrained portfolio is fully comparable. Even the SRI 5 portfolios have higher returns then the index itself. This result can be explained by the optimization procedure, which selects a subset of stocks that minimizes downside risk while maintaining return potential. In contrast, the Eurostoxx 50 index follows a fixed market capitalization weighting scheme that does not explicitly account for downside risk measures such as CVaR. We can observe the difference between the SRI 4 and SRI 5 return values, where the higher value corresponds to a riskier (more volatile) portfolio composition. At the same time, the portfolio remains relatively concentrated, containing the smallest possible number of shares within the UCITS diversification constraints imposed. It is important to emphasize that the primary objective of the proposed methodology is not to maximize portfolio returns, but rather to construct portfolios that are consistent with the seven-level SRI risk classification used in financial regulation. The use of efficient frontier optimization therefore serves mainly as a tool for assigning representative portfolios to each SRI category. The higher portfolio returns observed in the empirical results can thus be interpreted as a secondary effect of the optimization procedure rather than the main goal of the proposed framework.

## 4.3 Comparison with traditional three-profile classification

When investing based on investment advisory, investors are classified into groups, the number of which is not precisely defined by regulation. These risk profiles were created to simplify the process of assessing the suitability test of an investor, which is required by the MiFID II directive. Based on this directive, investment firms providing investment advice are obliged to obtain relevant information about the client. This information mainly concerns the client's financial situation. Specifically, these are questions focused on the client's financial situation, the client's investment objectives, the client's knowledge and experience and risk tolerance before a specific financial instrument is recommended to him. The regulation itself does not specify a specific number of investor risk categories, nor does it determine which investment products should be assigned to a specific investor. In practice, many financial institutions use a three-profile classification of investors, which consists of a conservative, balanced and dynamic investor. This is a simplification of the advisory process, thanks to which it is subsequently possible to assign investment products to investors to wider groups of clients with different risk tolerances. This structure is also commonly used by Slovak financial institutions and banks providing investment advice. The same division of funds into three categories is used, for example, by the Austrian Erste Group Bank, which divides portfolios for conservative, balanced and dynamic investors. Within this approach, the investment funds are often interpreted according to wider risk intervals, which are based on the SRI risk indicator. The exact mapping between the client's investment profile and SRI is not formally standardized in no regulation or directive. In practice, it is common for SRI values to partially overlap between groups, as shown in Table 6. The same fund can thus be assigned to two different risk groups.

**Table 6: Comparison of Traditional Three-Profile Investor Classification and the Proposed SRI Based Classification**

| SRI | Typical Interpretation in Traditional Advisory (Three-Profile Model) | Investor Classification in the Proposed SRI Model |
|---|---|---|
| **1** | Conservative investor | SRI 1 investor |
| **2** | Conservative investor | SRI 2 investor |
| **3** | Conservative / Balanced investor | SRI 3 investor |
| **4** | Balanced investor | SRI 4 investor |
| **5** | Balanced / Dynamic investor | SRI 5 investor |
| **6** | Dynamic investor | SRI 6 investor |
| **7** | Dynamic investor | SRI 7 investor |

Source: Authors' own elaboration

Table 6 shows the traditional approach in the second column, where SRI risk intervals are assigned to three risk profiles. Our approach is located in the third column and assigns each investor a specific SRI value. This value characterizes the riskiness of both the investor and the recommended investment product. Such an assignment of risk groups, which has been used so far, is not precisely defined by regulation and may differ between individual financial institutions. At the same time, if we consider a dynamic investor, he may be assigned a fund with an SRI value of 5, but also a fund with an SRI value of 6 or 7. From a risk perspective, this is a significant difference, as can be seen in Table 1. Advantage of this approach is not necessarily higher portfolio performance, but more accurate alignment of the investor's risk tolerance with the risk classification of investment products. Reducing the risk intervals increases the transparency of the investment recommendation. This prevents two investors with the same SRI group from investing in products with different levels of risk. The proposed approach eliminates this problem by assigning each investor a unique SRI value that is directly linked to the riskiness of the recommended investment portfolio or product. The investor is thus classified into one of seven groups, with the same SRI value also characterizing the riskiness of the recommended investment solution. This ensures a direct and transparent link between the investor's risk profile and the regulatory risk classification of investment products. The main advantage of this approach lies in a more accurate alignment of the investor's risk tolerance with the risk classification of investment products. At the same time, the risk of a situation where two investors with the same risk profile invest in products with significantly different levels of risk is minimized.

It is important to emphasize that the primary goal of the proposed methodology is not to improve portfolio returns, but to provide a more precise framework for linking investors' risk profiles to the seven-level SRI classification used in financial regulation. The construction of the portfolio based on the efficient frontier represents a further step that allows the assignment of portfolios to each SRI category. In practice, the exact portfolio construction methods used by financial institutions are not publicly available and may differ across advisory providers. Therefore, for comparison purposes we approximate the traditional three-profile classification by grouping SRI categories into conservative (SRI 1–3), balanced (SRI 3–5) and dynamic (SRI 5–7) investors as shown in Table 6. Missing portfolios that are not on the efficient frontier and their risk is lower than the efficient lowest risk portfolio are build on the combination of the lowest risk portfolio and risk free asset. The exact value of each component is computed by the ratio based on the VEV(13). This approximation allows us to illustrate how the proposed seven-category classification provides a more granular alignment between investor risk tolerance and portfolio risk compared with the traditional three-profile framework.

## 5. Discussion

The work achieved several results that contribute to improving the approach to investors and the classification of their risk. We designed an investment questionnaire using Fuzzy logic that meets the requirements of MiFID. Based on this questionnaire, we evaluated the answers that the investor must fill in based on his specific values (not according to the filled-in answer options). This approach is so specific for each investor as it focuses on the current real-life situation of the investor and dynamically adapts based on the values answered. The investment questionnaires that have been used so far are static and consist of their predefined answers, from which it is often possible to read how the investor should answer in order to achieve the highest possible score (often this is the last value). This approach used so far is not connected to the 7 risk values (SRI) that evaluate the riskiness of funds, and it is therefore not possible to assign investors the riskiness of the fund that they exactly correspond to. After creating the questionnaire and answering the answers, we proceeded to construct the portfolio using CVaR minimization. For each type of SRI, we constructed a portfolio that has the lowest available CVaR value. The advantage of using UCITS conditions when constructing portfolios is that portfolios must contain at least 17 components and the maximum weight of one stock can be no more than 10%. In this way, we avoid the problem of low diversification, which could occur if we constructed portfolios only based on risk minimization.

# 6. Conclusion

Investing is and will always be an attractive topic for the public. In this article, we focused on the investment process from the arrival of the investor, through classification into a risk group using SRI and subsequent assignment of a portfolio optimized by minimizing CVaR. The advantage of the approach using Fuzzy logic was the possibility of more accurate classification of the investor into one of seven risk groups. This approach provides flexibility in setting questions and a closer understanding of the current investment status of each client separately. This eliminates the inaccuracy in investor classification using universal questionnaires, where there is a higher error rate, since investors can purposefully choose answers that do not correspond to their risk profiles. By creating a Fuzzy SRI matrix, we constructed a recommendation on how the final value of the investor's risk profile can be approached. Since the whole process is dynamic and a similar setting does not yet exist, it can be examined in the future and the matrix re-evaluated according to needs. After classifying the investor, we created effective portfolios from shares of the Eurostoxx 50 index. From these portfolios, we selected optimal portfolios for SRI groups based on CVaR minimization. For each available group, we selected a portfolio that is effective using the restrictive conditions of UCITS, which ensure a certain degree of investor protection. The result was 7 effective portfolios that are adapted to real conditions and comply with European standards. In addition to portfolio construction, in the work we also compared the SRI and SRRI approaches and pointed out the shortcomings of the currently provided investment questionnaires, which have low informative value. In further research, we could imagine continuing this topic enriched with active portfolio management, for example, using elements of artificial intelligence, which would predict the optimal portfolio after quarters.

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# Appendix

## Investment Questionnaire Structure

The parameters in the questionnaire may vary depending on the country. A typical example is the first question where in the parameters column we provide data for Slovakia. The investment questionnaire used in this study consists of four groups of questions focusing on the investor's financial situation, investment goals and preferences, ability to bear risk and losses, and investment knowledge and experience. The first three groups of questions serve as inputs for the fuzzy risk evaluation. The fourth group of questions is included primarily to satisfy regulatory requirements of the MiFID II directive and is used to assess the investor's knowledge and experience. These questions do not enter the fuzzy calculation because their answers cannot be directly represented by fuzzy membership functions. The parameters used in the investment questionnaire are calibrated primarily for a typical Slovak retail investor. However, these parameters can be adjusted for different countries in order to better reflect local economic conditions and income levels. For example, the threshold values used in the first question evaluating monthly income are derived from publicly available statistics of the Statistical Office of the Slovak Republic for the year 2024. In other countries, these thresholds can be modified according to the corresponding national income statistics.

**Table A1: Investment Questionnaire Structure**

| Question | Category | Fuzzy Set Type | Parameters |
|---|---|---|---|
| **Net monthly income** | Financial situation | Fuzzy R | a = €615, b = €1,130. Values correspond to the minimum net wage and the average net wage in Slovakia in 2024. |
| **Monthly financial surplus after expenses** | Financial situation | Fuzzy R | a = 0, b = 10% of the income reported in first question. If the surplus is lower than €20, the membership value equals 0. |
| **Total financial reserve** | Financial situation | Fuzzy R | a = €615, b = six times the income reported in first question (representing approximately six months of income). |
| **Total value of assets** | Financial situation | Fuzzy R | a = six times the income reported in first question, b = twenty-four times the income reported in first question (representing approximately two years of income). |
| **Monthly debt and loan repayments** | Financial situation | Fuzzy L | a = 36%, b = 43% of income. These values represent recommended maximum debt-to-income ratios according to financial planning guidelines (Crace, 2024). |
| **Main investment objective** | Investment goals and preferences | Discrete membership | "Only small fluctuations tolerated" = 0; "Low risk acceptable" = 0.2; "Higher risk acceptable for higher return" = 0.8; "High growth potential preferred" = 1. |
| **Planned investment horizon** | Investment goals and preferences | Fuzzy R | a = 0 years, b = 5 years. Five years represents the commonly recommended minimum investment horizon used by financial institutions. |
| **Percentage of monthly surplus willing to invest** | Investment goals and preferences | Fuzzy R | a = 25%, b = 50%. Values represent the proportion of disposable income allocated to investment. |
| **Stability of income** | Risk tolerance | Singleton | m = 1 if income is regular, otherwise m = 0. |
| **Reaction to a 20% portfolio loss** | Risk tolerance | Singleton | m = 1 if the investor continues or increases the investment, otherwise m = 0. |
| **Maximum tolerable investment loss** | Risk tolerance | Singleton | m = 1 if the investor can tolerate up to 100% loss without existential financial problems. |
| **Age** | Risk tolerance | Fuzzy L | a = 54 years, b = 64 years. These values correspond to the typical age range before retirement. |

| | | | |
|---|---|---|---|
| **Investment experience** | Knowledge and experience | Multiple options Not used in fuzzy calculation | Possible answers: Yes / No |
| **ESG preference** | Knowledge and experience | Multiple options Not used in fuzzy calculation | Possible answers: Yes / No |
| **Financial instruments understood** | Knowledge and experience | Multiple options Not used in fuzzy calculation | Possible answers: ETF, Mutual funds, Stocks, Bonds |
| **Investment instruments previously used** | Knowledge and experience | Multiple options Not used in fuzzy calculation | Possible answers: ETF, Mutual funds, Stocks, Bonds |

Source: Authors' own elaboration