Určenie rizikovej skupiny investora fuzzy logikou pri využití európskej regulácie UCITS

Determining investor's risk group using fuzzy logic under the UCITS

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Abstrakt

Existuje mnoho prístupov, ktoré skúmajú členenie rizika investora. Najčastejšie používaným prístupom správcovských spoločností a brokerov je investičný dotazník, ktorý určuje rizikovú skupinu, do ktorej investor patrí. Častým problémom tohto prístupu je, že potenciálny investor je plne zaradený do jednej kategórie, aj keď môže byť blízko hranice s druhou kategóriou. Tento nedostatok je možné zlepšiť pomocou využitia európskej smernice o podnikoch kolektívneho investovania do prevoditeľných cenných papierov (z angl. UCITS), ktorá stanovuje 7 rizikových skupín podľa syntetického ukazovateľa rizika a strát SRRI. Využitím fuzzy logiky, určujeme s akou príslušnosťou investor spĺňa každú jednu otázku. Je tak možné presnejšie definovať profil investora cez SRRI vyššou granularitou rizikových skupín. Na analýzu používame programovací jazyk Python v prostredí Jupyter Notebook. Tento článok má za cieľ priniesť presnejšiu klasifikáciu investorov do rizikových skupín, nakoľko tvorba investičného dotazníka fuzzy logikou s využitím európskej smernice ešte doposiaľ nebola implementovaná.

Kľúčové slová

UCITS, Fuzzy, Manažment rizika, SRRI

Abstract

There are many approaches that examine the classification of investor risk. The most used approach offered by asset management companies and brokers is an investment questionnaire, which determines the risk group to which the investor belongs. A common problem with this approach is that a potential investor is fully classified into one category, even though he may be close to the border with the second category. This deficiency can be improved by using the European Collective Investment in Transferable Securities directive (UCITS), which sets out 7 risk groups according to the synthetic risk and loss indicator SRRI. Using fuzzy logic, we determine with what affiliation the investor meets each question. This makes it possible to more accurately define the investor profile through SRRI with a higher granularity of risk groups. The Python programming language in the Jupyter Notebook environment is used for the analysis. This article aims to bring a more accurate classification of investors into risk groups, since the creation of an investment questionnaire with fuzzy logic using the European directive has not yet been implemented.

Key words

UCITS, Fuzzy, Risk management, SRRI

JEL classification

C44, G11, G18

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1 Introduction

Allocating an investor's assets and assigning them to an adequate risk group is a difficult task in modern investing. Investors often demand the highest returns, the risk of which they are unable to manage. It is the failure to manage risk (market fluctuations) that leads to the sale of assets in a period of unfavorable development of financial markets and subsequent high losses. In order to set up a suitable investment product for a potential investor, it is necessary to classify investor according to the risk profile and assign investor to a risk group, as defined in the Securities Act 566/2001 Coll (Národná rada Slovenskej republiky, 2001). Investment questionnaires in banks, asset management companies and other asset providers in Slovakia are carried out based on so-called exclusionary conditions (hereinafter K.O. conditions), which integrate the investor into one of the three risk groups. If the questions in the questionnaire are answered in favor of high-risk aversion, the investor is rightly limited in his choice and is subject to a restriction on the allocation of his assets to more risky funds. The disadvantage of questionnaires using this approach is that they assign investors to only 3 risk groups, which is often not enough. As mentioned, investors are sorted into group of dynamic investors, balanced investors and conservative investors. The first group to represent investors with the greatest risk aversion is the group of conservative investors. These investors are allowed to buy bonds and bond funds due to their low risk. Bonds provide a fixed income in the form of interest rates, which can help protect investors from inflation. In the event of bankruptcy, bondholders are paid before shareholders (Johnson, 2018).

For investors who are willing to take on a greater degree of risk, there is a set for balanced investors, which represents a mixed approach, consisting of bond, real estate, and equity parts. The last set stands for dynamic investors, these investors have a high level of risk acceptance and can thus achieve the highest returns. This set allows investors to create a portfolio from all available assets and the allocation is usually fully focused on stocks. Companies and financial advisors use terms such as conservative, balanced and dynamic investors to describe investment strategies and portfolios that correspond to clients' different levels of risk tolerance and investment objectives. These terms are not defined in the law but are commonly accepted in the investment community and their meaning is derived from related EU legislation and rules, such as MiFID - Markets in Financial Instruments Directive (European Parliament and Council, 2004). They often appear in investment literature and educational materials (Omololu, E, 2023).

The current deficiency of investment questionnaires results is assigning different investors to the same set, while they may be investors who have significantly different levels of risk acceptance or risk aversion. It is possible to have an investor that is on the border of two groups and therefore his portfolio composition should overlap between these groups. However, since the currently used questionnaires strictly categorize investors only into 3 groups, the investor that falls in between will end up with a sub-optimal recommendation of portfolio composition since the range of risk aversion in specific group is too big. An option is to create more risk classes as defines UCITS, which stands for Undertakings for collective investments in transferable securities (European Parliament and Council, 2014). To solve this problem, this article applies fuzzy logic and fuzzy sets to assign the exact allocation of assets, specifically adjusted to the investor's responses. The next problem is uncertainty in answers, when respondents are not sure which answer to choose, so they can pick random answers from provided answers which influence the results. This problem will be solved with more specific answer options represented with fill-in answer options, instead of multiple predefined options.

2 Methodology

This chapter examines the current state of questionnaires and analyzes the assignment of investors to risk groups. At the same time, we will describe why the current setup is insufficient. The second subchapter describes the fuzzy set approach that will be used to refine the allocation to be specific and fitting to each investor. Final subchapter takes into consideration UCITS regulation for European Union funds and used formulas for computing each risk class.

2.1 Usage of the Investment Questionnaires

The first chapter discusses the reason for using the investment questionnaire. This questionnaire is a necessity for starting the investment and its creation must comply with the Securities Act 566/2001 Coll. From the results of the questionnaires, it is possible to purchase only those underlying assets whose risk corresponds to the risk profile of the investor. By buying riskier assets beyond their level of risk acceptance, the investor exposes themselves to the danger of not managing emotions and fluctuations in the markets, due to which the portfolio may be sold at a loss (Financial Conduct Authority, 2021).

The current solution for these questionnaires is to use classical sets, where restrictive K.O conditions determine the result of the questionnaire and each of the investors can belong to only one set. In general, if an investor is unable to take risks when investing, he belongs to a conservative investor. If an investor is willing to take the highest risk, he is classified as a dynamic investor. If the investment questionnaire consisted of only one question in the wording: indicate your risk aversion when investing, it would be possible to distinguish between the two investors and assign them to appropriate groups. Let us denote by the letter X a universal set of elements (in our case all potential investors) and the set C (in our case a subgroup of investors) as a subset of the set X. Based on set theory, one can say whether each element x of the universal set X belongs to the set C. The belonging of the element x to the set C, which is a subset of the universe X, (which is a basic mathematic concept developed in (Cantor, 1874) is expressed by a characteristic function φ_K as follows:

$$
\begin{gathered}
\varphi_K : X \rightarrow \{0, 1\}, \\
\varphi_K\,(x) = 1, if\ x\ \in C, \\
\varphi_K\,(x) = 0, \text{if } x\ \notin \mathrm{C}
\end{gathered}
\tag{1}
$$

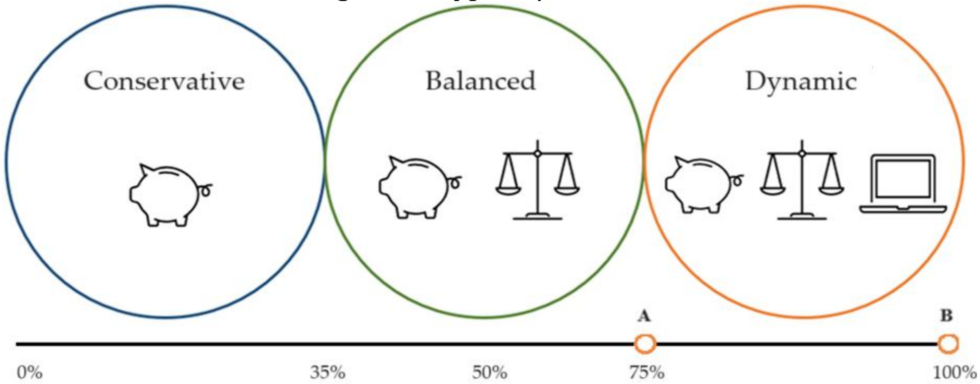
In this case, set C could represent a group of conservative investors with maximum risk aversion, and element x is the representative of the investor who filled out the investment questionnaire. Based on the answers, investors are assigned a percentage of risk, based on which it is possible to include the investor in a risk group. In general, percentages in a portfolio can be used to determine an investor's risk profile. A conservative investor might have a higher share of conservative investments, such as bonds or money markets, while a dynamic investor might have a higher share of stocks or other riskier assets. These ratios can be adapted to the individual goals and needs of the investor (Nukala, V.B., Prasada Rao, S.S, 2021). When identifying, for instance, conservative investors, the characteristic function could be determined as follows:

$$
\begin{gathered}
\varphi_C\,(x) = 1, \text{if } x \leq 35\%, \\
\varphi_C\,(x) = 0, \text{if } x > 36\%
\end{gathered}
\tag{2}
$$

Investment questionnaires set out three sets to which investors can be assigned. The boundaries of each set are shown in Figure 1, where:

- Conservative investor achieves a result from 0% to no more than 35%
- A balanced investor achieves a result of at least 36% to no more than 74%
- A dynamic investor achieves a result of at least 75% to 100%

Figure 1: Types of investors



Source: Own processing (2025)

Based on the questionnaire, individual investors are assigned to classes and therefore can buy securities, the composition of which varies depending on their risk group. Investors in the higher risk group have the opportunity to buy products from their own risk group and as well the products available to the lower risk groups. If the product were only available to the riskiest group, conservative investors would not have access to it. At first glance, these three groups may seem sufficient. However, there is a difference that would be best shown by an example of two investors. Let both investors be in the set of dynamic investors, but investor *A* has a significantly lower risk acceptance (75%) - on the border with a balanced investor. Investor *B* is fully dynamic and has a maximum risk acceptance rate (100%). According to the investment questionnaire, both would be offered the same products in identical proportions as they both belong to the dynamic investor group. This article tends to disagree with this approach, as each of the investors is specific and their portfolios should be more personalized, based on their risk profile. The inaccuracy of this approach can be easily read from Figure 1. For this reason, this article will explore the application of fuzzy logic in order to improve the categorization of investors based on the results of their investment questionnaire.

2.2 Fuzzy logic

Fuzzy logic was introduced as an extension of classical sets (Zadeh, 1965). The difference from the classical sets lies in determining belonging to the set on the interval between 0 and 1. In the example above, the allocation of investors in a given set using classical sets could not be clearly distinguished, resulting in different investors being recommended the same portfolio composition. Using intensities (affiliations) of belonging to a set, it is possible to determine the exact values of affiliations of belonging and thus better optimize the asset allocation for a given investor. If fuzzy logic was used, the investor could have specific portfolio type with higher granularity and so it would be much more precise than using only three risk groups. We can distinguish between conservative and ultra conservative investors and their risk aversion.

A high variety of fuzzy sets exist. In this work, we applied: R-fuzzy, L-fuzzy, triangular, trapezoidal, and singleton. Each of the sets has a specific and suitable applicability for calculating affiliations.

R fuzzy is defined with two parameters. Parameter a represents, where support of fuzzy set starts and parameter b represents where core of fuzzy set starts (3).

$$\mu_R(x) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{b-a}, & a < x < b \\ 1, & x \geq b \end{cases} \tag{3}$$

L fuzzy is defined with two parameters. Parameter a represents, where core of fuzzy set ends and parameter b represents where support of fuzzy set ends (4).

$$\mu_L(x) = \begin{cases} 1, & x \leq a \\ \dfrac{b-x}{b-a}, & a < x < b \\ 0, & x \geq b \end{cases} \tag{4}$$

Singleton (S) fuzzy is defined with one parameter. Parameter m represents an element, from all elements that assumes the value of one – the core of fuzzy set is defined in only one point (5).

$$\mu_A(x) = \begin{cases} 0, & x \neq m \\ 1, & x = m \end{cases} \tag{5}$$

Trapezoidal (Trap) fuzzy is defined with four parameters. Parameter a represents start of support, d represents end of support, b represents start of the core, c represents end of the core.

$$\mu_A(x) = \begin{cases} 0, & x \leq a \lor x \geq d \\ \dfrac{x-a}{b-a}, & x \in (a,b) \\ 1, & x \in < b,c > \\ \dfrac{d-x}{d-c}, & x \in (c,d) \end{cases} \tag{6}$$

More about fuzzy sets theory is in Fuzzy set theory and its applications can be found in multiple articles such as (Zimmermann, 2001).

2.3 UCITS

UCITS represent a European Union regulatory framework governing collective investment funds. It was introduced to ensure a level of investor protection and to ensure the free distribution of these funds within the EU. UCITS funds are popular with both retail and professional investors, who must comply with strict rules on diversification, transparency and risk management.

UCITS regulations require a key investor information document (KIID), which contains important information about the fund, including the investment strategy and risk profile. It is in this document that the Synthetic Risk and Reward Indicator is found. This indicator is mostly used with funds that are offered to retail investors. The SRRI was introduced, to simplify the information for investors in matter of potential riskiness and return of the specific fund.

SRRI as an indicator was introduced as part of EU legislation on the key documents that must be shared with investors, and they contain important information about the fund. This indicator is a mandatory part of the KIID for all Undertakings for Collective Investment in Transferable Securities (UCITS) funds. As shown, the intention of SRRI is to provide simple, visually accessible information, which makes it easier for investors to compare different investment products. Another benefit of SRRI is its transparency of the fund score, which is widely used with brokerage companies which intention is to provide funds for their clients, which matches clients' risk profile. The higher the score of SRRI is, the higher risk and return can investors expect. SRRI is expressed through a single number that ranges from 1 to 7. This level reflects different levels of risk, with a lower number meaning lower risk and lower return, while a higher number means higher returns. 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. Volatility is used as the main indicator of risk, which is measured with standard deviation for last 5 years. It reflects how significantly an investment can change over time.

Score from 1 to 2 (marginally 3) belongs to the funds with lower risk. Typically, they invest in low-risk assets like government bonds, term deposits, short-term bonds, or other cash equivalents. Such funds are often referred to as conservative or suitable for conservative investors.

The score from 3 to 5 belongs to the funds with higher risk. These funds are likely to have structure based on combination of bonds, stocks and other financial instruments. Bond do not have to be just issued by government. Higher risk bonds with higher yields are corporate bonds, which might be contained in these compositions. These funds are suitable for balanced investors, which cannot manage high risk funds.

Score from (marginally 5) 6 to 7 are two of the highest possible scores from SRRI range. High risk funds mostly allocate their financial means into stocks or other riskier assets. These funds have the tendency for the long period of time to have higher returns than funds with conservative assets like government bonds or funds that generate income from real estate's rents.

The volatility on which the SRRI is calculated is measured using the historical standard deviation of the fund's returns. Standard deviation measures how much a fund's returns deviate from the average return over a period. A period of 5 years of historical data is usually used to calculate the SRRI, if available. General methodology is shown in Methodology for the calculation of the synthetic risk and reward indicator (Committee of European Securities Regulators, 2009). According to the Committee the volatility of the fund shall be computed, and then rescaled to a yearly basis, using the following standard method:

$$volatility = \sigma_f = \sqrt{\frac{m}{T-1}\sum_{t=1}^{T}\left(r_{f,t} - r'_f\right)^2} \tag{7}$$

Where the returns of the fund ($r_{f,t}$) are measured over T non overlapping periods of duration of $1/m$. This means m=52 and T = 260 for weekly returns, and m=12 and T=60 for monthly returns; and where r'_f is arithmetic mean of the returns of the fund over the T periods:

(8)

$$r'_f = \frac{1}{T}\sum_{t=1}^{T} r_{f,t}$$

Committee states that the synthetic risk and reward indicator will correspond to an integer number designed to rank the fund over a scale from 1 to 7, according to its increasing level of volatility. Each score from 1 to 7 represents the final value behind the volatility intervals:

Figure 2: Types of investors

Risk Class	Volatility Intervals	
	equal or above	less than
1	0%	0.5%
2	0.5%	2%
3	2%	5%
4	5%	10%
5	10%	15%
6	15%	25%
7	25%	

Source: own processing (2025)

3 Results

We can divide questions in an investment questionnaire into three groups. First group A represents questions focused on investor's experience and knowledge with securities. The second group represents the financial situation of the investor. The last third group focuses on the risk and time horizons of investors.

Here are the questions asked in the questionnaire, where all answers have been filled by option "fill in blank" and not with using predefined options:

Q1A-Right: How many years of experience do you have in investing?

- Where a stands for zero experience, b stands for 3-year experience (3).

Q2A-Trapezoidal: What is the percentual annual return of S&P500 index in the last 10 years?

- Where a stands for 7% return, b stands for 8% return, c stands for 12% return, d stands for 13% return (6).

Q3A-Singleton: What is my portfolio value when I invested 1 000 units, the first year dropped by 10% and second year rose 10%?

- Where m stands for 990 units (5).

Q1B-Right: What is your average monthly net income?

- Where a stands for 615 representing minimum net wage for Slovak citizen, b stands 1130 representing average net wage of Slovak citizen (3).

Q2B-Right: What amount can you save monthly?

- Where a stands for 0 units, b stands for 10% of net wage from Q1B (3).

Q3B-Right: What is your total amount of savings reserve?

- Where a stands for 0 units, b stands for value of 6 times of net wage from Q1B (3).

Q4B-Left: How much do your loans cost monthly?

- Where a stands for value of 36% of net wage, b stands for value of 43% of net wage from Q1B (4).

Q1C-Right: How many years do you plan to invest?

- Where a stands for 3 years, b stands for 5 years (3).

Q2C-Left: If the value of your portfolio dropped 20% in a year, how many percent of total portfolio would you sell.

- Where a stands for 0%, b stands for 5% of portfolio value (4).

Q3C-Left: What is your age?

- Where a stands for 54 years, b stands for 64 years of age (3).

As the input we provide randomly generated data that simulates real answers. This input data from the investment questionnaire is shown in figure 3 below, where we represent 481 records:

Figure 3: Investment questionnaire records

	A	B	C	D	E	F	G	H	I	J
1	Q1A-R-exp	Q2A-TRAP-sp500	Q3A-S-drop	Q1B-R-income	Q2B-R-save	Q3B-R-savings	Q4B-L-loan	Q1C-R-horizon	Q2C-L-drop	Q3C-L-age
2	6	7	957	2243	236	10467	40	16	0	49
3	16	10	1058	2022	509	1348	45	12	13	37
4	16	14	1088	2076	247	14532	31	3	9	68
5	9	14	990	1503	520	10020	22	26	0	24
6	12	12	961	2235	62	15645	32	15	10	25
7	18	6	990	1302	279	13888	21	2	0	50
8	6	4	999	1160	343	18947	0	18	0	22
9	15	7	1075	844	59	7877	34	20	14	18
10	6	10	1092	1250	108	12500	0	17	11	18
11	3	4	1029	1814	217	22373	0	5	0	37
12	8	8	990	1171	276	14833	39	19	0	44

Source: own processing (2025)

After obtaining answers we use the fuzzy logic which sets the affiliation to each fuzzy set. Used formulas in Python are represented at figure 4, which is equal to formulas defined in subchapter 2.2. In the whole process we used the programming language Python.

Figure 4: Fuzzy sets

```python
def L_fuzzy(a,x,z):
    if (x<=a):
        return 1
    elif (a<x and x<z):
        return (z-x)/(z-a)
    elif (x>=z):
        return 0
```

```python
def R_fuzzy(a,x,z):
    if(x<=a):
        return 0
    elif(a<x and x<z):
        return (x-a)/(z-a)
    elif(x>=z):
        return 1
```

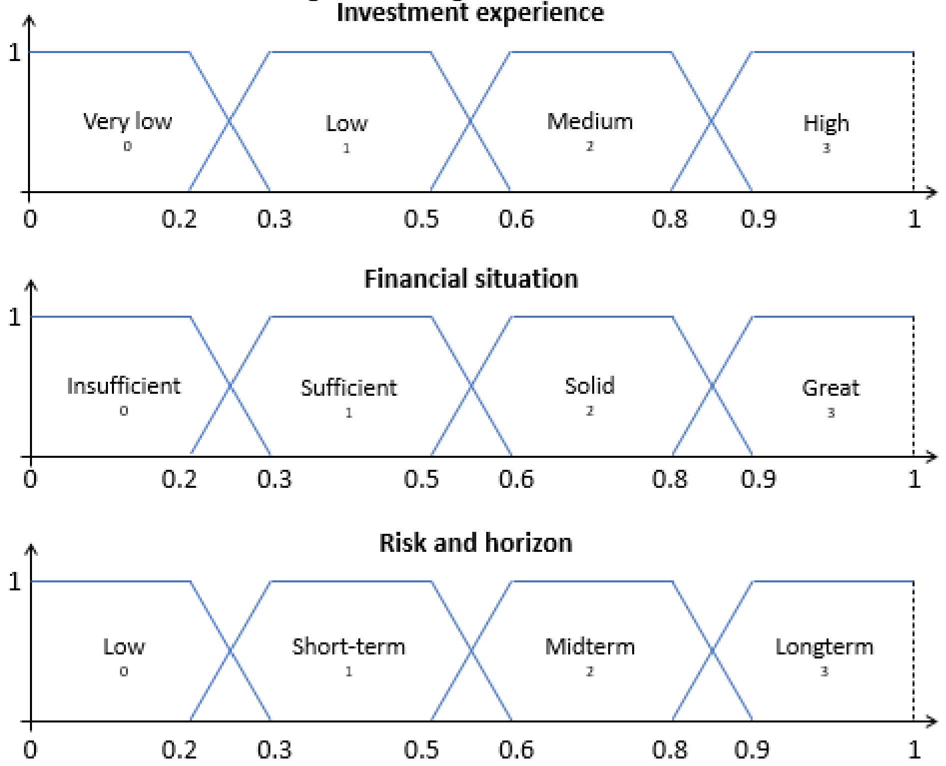
```python
def S_fuzzy(x,m):
    if(x!=m):
        return 0
    elif(x==m):
        return 1
```

```python
def Trap_fuzzy(a,l,x,r,z):
    if(x<=a or x>=z):
        return 0;
    elif(x>a and x<l):
        return R_fuzzy(a,x,l)
    elif(x>=l and x<=r):
        return 1
    elif(x>r and x<z):
        return L_fuzzy(r,x,z)
```

Source: own processing (2025)

After the computation is done, we proceed to averaging the responses of individual groups to new three groups QA, QB, QC. These values we substitute with the use of linguistic variables as shown at Figure 4, which are used in our built matrix which determines the final SRI score.

Figure 5: Linguistic variables



Source: own processing (2025)

The matrix is filled with 64 possible options and 7 outputs. The matrix used does not have a specific general notation. Since this is a new approach, we have proposed the notation in the following figure 6.

Figure 6: Defined SRRI matrix

INPUT	SRRI	INPUT	SRRI	INPUT	SRRI	INPUT	SRRI
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	7
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	7
0,3,3	4	1,3,3	6	2,3,3	7	3,3,3	7

Source: own processing (2025)

The last step was to show the SRRI score from 1 to 7 range and compare it with three risk groups used until now. This is shown at figure 7.

Figure 7: Output of investment questionnaire

	Q1A-R	Q2A-TRAP	Q3A-S	Q1B-R	Q2B-R	Q3B-R	Q4B-R	Q1C-R	Q2C-L	Q3C-L	QA	QB	QC	JP-A	JP-B	JP-C	SRRI	SRRI_profile
0	1	0	0	1	0.03	1	0	1	0	1	0.33	0.51	0.67	Low	Sufficient	Midterm	3	Balanced
1	1	1	0	1	0.05	1	0	1	0	1	0.67	0.51	0.67	Medium	Sufficient	Midterm	4	Balanced
2	1	0	0	1	0.07	1	0	1	0	1	0.33	0.52	0.67	Low	Sufficient	Midterm	3	Balanced
393	1	0	0	1	0.1	1	0	1	0	1	0.33	0.52	0.67	Low	Sufficient	Midterm	3	Balanced
394	1	1	1	1	0.04	1	0	1	1	1	1.0	0.51	1.0	High	Sufficient	Longterm	6	Dynamic
395	1	1	0	0.33	0.13	1	0	1	0	1	0.67	0.36	0.67	Medium	Sufficient	Midterm	4	Balanced
396	0.67	1	1	1	0.06	1	0	1	0	1	0.89	0.52	0.67	High	Sufficient	Midterm	5	Balanced
397	1	1	1	1	0.04	1	0	1	0	1	1.0	0.51	0.67	High	Sufficient	Midterm	5	Balanced
398	0.33	0	0	0	0.07	0	0	1	0	1	0.11	0.02	0.67	Very low	Insufficient	Midterm	2	Conservative
399	1	0	1	1	0.02	1	0	1	0	1	0.67	0.5	0.67	Medium	Sufficient	Midterm	4	Balanced
400	1	0	0	0	0.22	0	0	1	0	1	0.33	0.06	0.67	Low	Insufficient	Midterm	2	Conservative
401	1	0	1	0.71	0.06	1	0	1	1	1	0.67	0.44	1.0	Medium	Sufficient	Longterm	5	Balanced

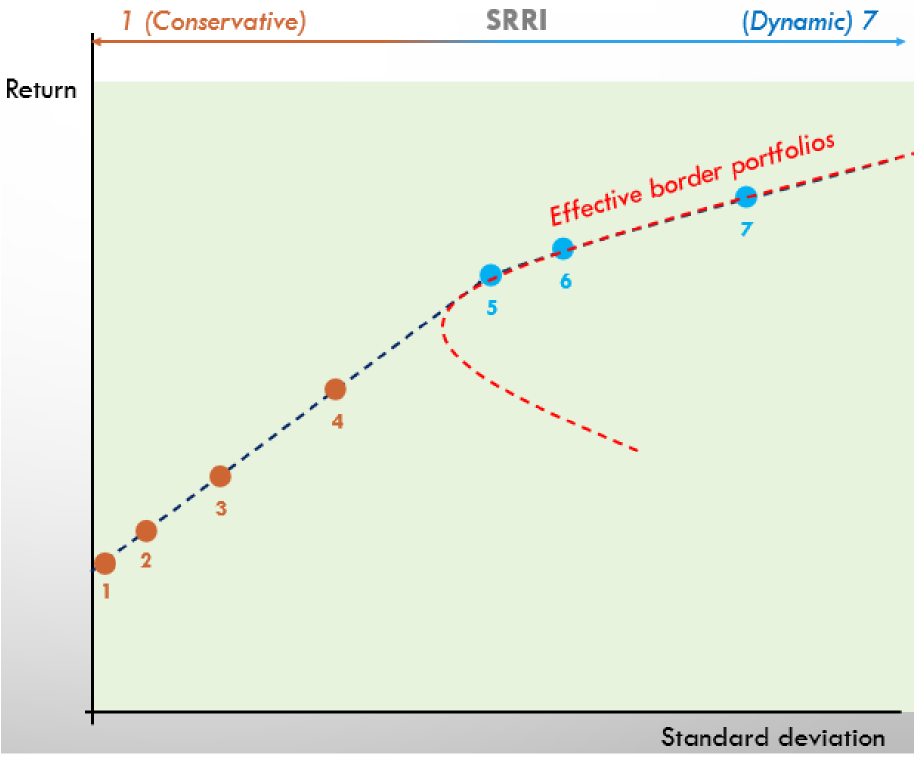
Source: own processing (2025)

With this approach, we can precisely define how risky a fund is ideal for an investor and more precisely determine the risk profile using SRRI.

4 Further research

There are many ways to build a portfolio based on set value of risk. If we were to try to adhere to the European regulation for collective investment UCITS, we should continue in our research to use the standard deviation as a representative of risk while building portfolios. In this case, it is possible to use the theory of modern portfolio, where it is possible to create an effective border of portfolios with standard deviation on horizontal axis and estimated return on vertical axis. We can subsequently divide these portfolios, which would be made up of equity securities, into SRRI risk groups according to the interval of the lower and upper volatility limits. This allows us to build groups of effective portfolios, which can then be optimized and the best portfolio for each group can be selected. Portfolios with lower SRRI classes must be combined with bonds or other low-risk assets. Here, it is possible to start, for example, from the possibility of using the capital market line and allocating the bond component, which represents a risk-free asset, in aliquots according to the degree of risk, while the capital market line will pass through the risk-free asset and the optimal portfolio, made up of purely equity assets. This approach shown at figure below is one of many that we are considering in the future as a complement to this work.

Figure 8: Effective border portfolios



Source: own processing (2025)

5 Conclusion

Risk management, portfolio selection and weight allocation is a challenging discipline and there is no clear answer to how to build an optimal portfolio that will perform best from all available options in future. A certain level of optimality can be reached by building a portfolio that is more individualized for the investor. The original format of the investment questionnaire assigned investors to one from three categories only. Here existed edge cases and not specifically defined sets of who and when is going to be assigned in specific risk set. An alternative proposed in this article is the applicability of fuzzy sets, where affiliations to individual sets based on answers from questionnaires can be assigned more accurately under the regulation UCITS. All restrictive conditions from answers in questionnaire are considered, using fuzzy sets and linguistic variables. We build the SRRI matrix with 64 specific options, that leads to 7 risk groups. The offered approach is more flexible, and the greatest advantage is the dynamism of questions, which are self-adaptable on each investor. The extension of this contribution could in the future involve applying a new approach that replaced the use of SRRI in 2014 with the current SRI approach found in Packaged Retail Investment and Insurance Products. The SRI approach is based on calculating a score from 1 to 7, taking into account market risk measure (MRM) and credit risk measure (CRM). In this approach, the calculation of volatility is applied using Value at Risk. The resulting portfolios would therefore not only depend on returns and standard deviation but also on the expanded model applied in the SRI methodology.We believe our new approach for evaluation of investors' risk is more accurate and transparent.

Funding: This article was supported by the Grant Agency of Slovak Republic: VEGA grant no. 1/0120/23 “Environmental models as a tool for ecological and economic decisions making”.

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