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Behavioural Aspects of the Financial Decision-Making

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Background and Purpose: Behavioural finance is a relatively new, but rapidly evolving field that provides explanations of an economic decision-making by cognitive psychology, conventional economic and financial theory. Behavioural finance searches the influence of psychology on the behaviour of financial practitioners and the subsequent effects on the financial markets. The purpose of the paper is the research on behavioural aspects of financial decision-making as they help explain why and how markets might be inefficient.
Design/Methodology/ Approach: Fuzzy logic is an excellent tool for working with linguistic variables that are often found when working with behavioural data. Thus, we analyse the financial decision-making process from the perspective of behavioural finance aimed at better understanding of the decision-making process of investors applying the principles of fuzzy logic to solve various financial problems.
Results: The results of the study indicate that fuzzy logic is applicable when solving problems of financial management and financial decision-making problems. The urgency of the fuzzy logic application for managerial and financial decisions should be emphasized. Research in this area indicates that in some cases, as in the case of behavioural financing, the use of fuzzy logic is far more suitable than the use of other methods (Peters, Aguiar and Sales).
Conclusion: The novelty of the paper is to extend the application of fuzzy sets in the area of financial decision-making. The paper demonstrates that despite the fact, that fuzzy logic is currently used mainly in technical directions, it is applicable also in financial management, especially, in cases where it is necessary to consider the influence of human and the occurrence of linguistic variables.

Keywords: *behavioural economics; behavioural finance; fuzzy transform; fuzzy sets*

1 Introduction

Traditional finance uses models in which the market subjects are assumed rational, efficient and unbiased users of relevant information and whose decisions are consistent with utility maximization (Mendes-Da-Silva, et al., 2015: 10). The basic assumption of traditional finance is that all market participants, as well as the market itself, behave rationally to maximize their benefits (Sewell, 2007). Any investor who makes a non-optimal decision will be penalized by poor market outcomes. It is also true that the individual errors made by market participants are not correlated with each other and therefore these errors do not have the power to influence market prices. This rationality of market participants is one of the classic theories of the standard market: the efficient market hypothesis (Kliger and Van den Assem, 2014). Another basic concept is the relationship between expected profit and risk: risk-averse market subjects demand greater profits for risky investments.

The assumptions of traditional finance have unrealistic requirements in terms of human behaviour (Jay, 2003). Behavioural finance examines the impact of human constraints on decision-making (Nadanyiova, 2016). It also assumes that the financial market is under certain circumstances incompletely informed. Not all bad valuations of securities are caused by psychological influence. Some are also caused only by a temporary imbalance between demand and supply (Kercheval, 2012; Olah et. al., 2018).

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Thus, compared to traditional finance, behavioural finance is based on the alternative notion that investors, or at least a significant minority of them, are subject to behavioural biases, that means, their financial decisions can be less than fully rational (Xu, 2014). The main reason is that the features of cognitive psychology are applied in a financial context, e.g. overconfidence and over-optimism of investors‘ ability and the accuracy of the information; representativeness; conservatism; availability bias resulting from the overstatement of the probabilities of recent experienced events; frame dependence and anchoring; mental accounting and regret aversion (Richards, 2014).

Behavioural finance does not describe financial markets and market decision-making processes using mathematical models, but it is based on psychological observations and relies on the use of heuristics. Many assumptions of behavioural finance and most of the key concepts of the prospect theory are derived from experiments (Teichmann, 2015). There is usually no mathematical evidence for the results of these experiments, but many anomalies in the real financial markets can only be explained by behavioural finance findings. To name some of the anomalies, where only the psychological factors could be at work to explain the decision-making of investor, are the January effect, the effect of neglected stocks (this effect occurs on stock that is less liquid and tends to have minimal analyst support), the movement of stocks on the days of the week (months of the year), etc. The issue of investor sentiment and anomalies in cross-sectional stock returns is explored in the study of Stambaugh, et al. (2012) or Famma (1998). On the other hand, there are authors, who use relevant statistics and detail calculations and try to build the findings of behavioural economics into the model (Koszegu and Rabin, 2006; Smith, 1976). However, in general, the psychological factor and the effort to understand why the real market does not work as it should using the mathematical models of the traditional theory of finance have made the behavioural finances a field in which many practices and scenarios can be described by fuzzy logic.

To extend the knowledge on the behavioural finance, the main aim of this study is focused on the analysis of the behavioural finance using fuzzy sets. The novelty of the study is the search of the mutual connection between behavioural finance, i.e. financial decision-making and fuzzy sets, which is a subject of only a few researches, and thus its robust and deep study may bring a new model aimed at better understanding of the financial decision-making processes. Thus, the purpose of the paper is to judge the behavioural aspects in the financial decision making applying the principles of fuzzy logic.

The article is divided into four main parts. Literature review depicts the most important researches conducted in the field of the financial decision-making process from the perspective of behavioural finance. Methodology section explains the application of fuzzy logic principles and its basic assumptions. The application of fuzzy logic in conditions of the behavioural financing is solved in Results. The section Discussion, conclusions and recommendations underlines the role of the fuzzy logic in solving various problems of financial management and financial decision-making process, depicts the limitation of the study as well as the future direction of the research.

2 Literature Review

For quite a long time, financial decision-making followed only the traditional theory of finance, which basic principles include the fact that people choose from possible alternatives to maximize their expected profits (Holzer, 2017; Zhuravleva, 2017). The traditional theory considers an aversion to the risk of a given subject as an unchanging variable. Then in 1979, Tversky and Kahneman introduced the prospect theory describing, that people underweight outcomes that are merely probable in comparison with outcomes that are obtained with certainty; also, that people generally discard components that are shared by all prospects under consideration (Radin and Riashchenko, 2017). The prospect theory, which they confirmed by experiment, predicts a distinctive fourfold pattern of risk attitudes: risk aversion for gains of moderate to high probability and losses of low probability and risk seeking for gains of low probability and losses of moderate to high probability. Prospect theory explores how people choose from a variety of options (Friedman and Gerstein, 2017) and, on the other hand, assumes that people choose the alternative that will bring the greatest change in their wealth (Bureš et al., 2015). It means that people do not look at profits in absolute terms, but they measure the gain with respect to the reference point – property - at the beginning of the period (Marakova and Medvedova, 2016). The main differences between traditional theory and prospect theory are the perception of risk and the aversion to risk (Barberis and Thaler, 2003). In the prospect theory, aversion to risk varies according to how people perceive the change in their wealth. Kahneman and Tversky (1979) additionally assume that humans are naturally averse to the losses. The importance of their research findings was highlighted in the study of Costa et al. (2017) who claim the prospect theory is closely related to the issue of the behavioural finance, which has been a subject of various researches since 1990 when first scientific articles were published. The results have shown that few types of researches relating overconfidence, anchoring and confirmation biases to behavioural finances have been growing throughout the time.

Behavioural finance theory put psychology behaviour science theory into finance in order to use its pioneering view to re-examine investment behaviour in financial markets. However, Hoff and Stiglitz (2016) emphasize that not only psychology but also sociology and anthropology broaden economic discourse by importing insights into human behaviour. Behavioural finance assumes that individual financial decisions are influenced by emotions and mood (Rakovska and Svoboda, 2016). Many researchers studied the historical development of behavioural finance and its future research direction (Huang et al., 2016; Yang, 2016). Other important issues are devoted to the aspects of market investment behaviour (Khashanab and Alsulaiman, 2016), to the approaches that are helpful when trying to understand how financial markets perform (Bird et al., 2017) or to heuristic and biases in managerial decision-making under the risk (Houdek and Koblovsky, 2014).

Behavioural finance holds important implications for the practice of financial management and innovation (Zhang, 2009). The effect of individual psychology in investor decision making has to be considered while investment decision making is under the influence of personality, experience, judgement and special social relations, which can cause behavioural biases (Khoshnood and Khoshnood, 2011). The most important studies being carried out in the field of behavioural finance and trying to explain the investor sentiment in the stock market are the studies of Baker and Wurgler (2007), DellaVigna (2009) and Shiller (2003). The fact, that we are in a golden age of behavioural science (Cialdini, et al., 2018), makes the behavioural economics an important incentive to explain the irrationality of human decision-making.

A great deal of research on complex decision-making has been done in two separate fields: fuzzy logic and behavioural psychology. In behavioural psychology (and in its subset behavioural finance), we have an empirical evidence that people make decisions based on rules called heuristics (Peter, 1996). However, there is no mathematical model that would allow using this psychological knowledge. This issue is partly solved by fuzzy logic, a rigorous branch of mathematics that has been able to quantitatively formulate decision-making (Kovacova and Kliestik, 2017; Kliestikova et. al., 2017). The topic of the financial market modelling, decisions made on the market and related risk issues is a wide-ranging debate between fundamentalists and behaviourists. While the irrational traders are known by a shift in their sentiments, the rational ones have a limited capacity of arbitration. Hachicha et al. (2011) in their research investigates the development of a new modelling technique using fuzzy sets to explain the financial market dynamics perceived differently by fundamentalists and behaviourists. Mullor et al. (2002) adapted data envelopment analysis using the theory of fuzzy sets and fuzzy systems. Their results are pioneering as the system allows treating all imprecise and subjective variables which intervene in measuring the financial efficiency in public and private organisations. Casillas et al. (2004) suggested a new method to model the behaviour of customers using fuzzy sets. Their behavioural model is mostly used to explain the consumers´ changes in behaviour when making decisions, which can be easily applied in the sector of behavioural financing (Hryhoruk et al., 2017). The fuzzy methodology was used in the study of Michalopoulos et al. (2004) to select an optimal portfolio of government bonds. The model of fuzzy programming is used to specify the portfolio, which meets the investors´ requirements. Incorporation of fuzzy approaches to option price modelling is explained in the studies of Munoz et al. (2013) and Muzzioli and De Beats (2017). The analysis of investors´ expectations of financial development is depicted in the study of Barbera et al. (2008). Kim and Sohn (2016) proposed a fuzzy process to study psychological and behavioural attributes of entrepreneurs. Schjaer-Jacobsen (2004) portrayed and modelled the economic uncertainty using the fuzzy number; the research was enriched by the study of Pazzi and Tohmé (2004) who form a model of uncertainty in the financial crisis using the fuzzy risk rate.

The recent research in the financial sector, taking into account the fuzzy principles, is conducted in the area of risks. Kemaloglu et al. (2018) clarify the use of fuzzy logic to interpret dependent financial risks. The financial risks of projects are identified simulating the fuzzy system in the search of Bolos et al. (2015). It is obvious, that risk plays a key role in financial management, which forced Maciel et al. (2017) to research a way to measure risk exposure. As a result, they suggested an evolving possibilistic fuzzy modelling approach to estimate value at risk. Volatility modelling and forecasting are inseparable components of financial and risk management, thus an evolving fuzzy modelling approach for financial forecasting and financial market movements was developed by Maciel et al. (2016), Zgurovsky and Zaychenko (2016) or Vella and Ng (2014). The practical use of fuzzy logic and simulations in the decision-making process is declared in the survey of Chui and Ip (2017).

3 Methodology

We analyse the financial decision-making process from the perspective of behavioural finance aimed at better understanding of the decision-making process of investors applying the principles of fuzzy logic to solve various financial problems. We use this method to find out the level of the risk tolerance of clients and investors based on their annual income and total assets. We follow the problem of the investment policy determined by Bojazdiev and Bojadziev (2007) who assess the possible decision-making process of investors by three variables: risk tolerance ability, annual income and total networth. Fuzzy logic is used to demonstrate, that now only the conventional mathematical models are important in the sector of financial management as their application is rather questionable in the sector of financial and managerial systems, which involve many social and psychological factors. Fuzzy logic enables to describe these factors, uses logic operations and if- then inferential rules to find the conclusion. The paper proves that financial problem may be solved without traditional mathematical models, applying the heuristic principles.

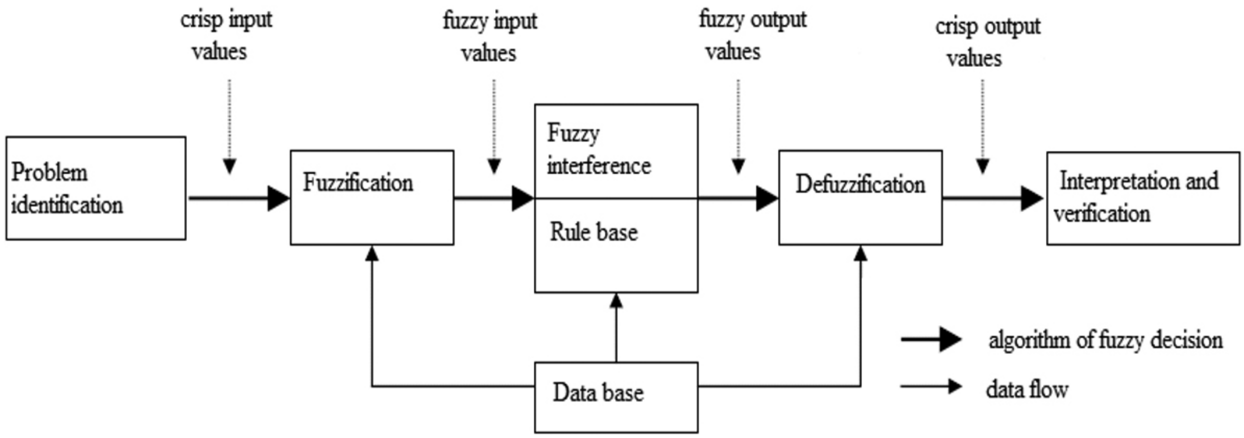

Figure 1: Algorithm of fuzzy decision

Fuzzy logic is a mathematical discipline, introduced by Lotfi Zadeh in 1965, which disproves the traditional assumption that in the area of general consideration some idea either belongs or does not to the consideration. It is a logic trying to be as close as possible to human thinking and perception. Dernoncourt (2013) states that fuzzy logic is based on the principle of fuzzy sets by introducing the notion of degree in the verification of a condition, enabling a condition to be in a state other than true or false and provides a very valuable flexibility for reasoning, which makes it possible to take into account inaccuracies and uncertainties. Fuzzy logic is an appropriate tool to work with data when we look for solutions that may not necessarily be the best, but can provide significant outputs, which is also one of the characters of behavioural finance. The study of Aquiar and Sales (2011) even shows that some behavioural heuristics are directly incorporated in the fuzzy algorithms.

The procedure of fuzzy processing is realized in several steps, as shown in Figure 1 (Dostál, 2012).

Firstly, the input and output variables are to be modelled. In fuzzy problems, these data are often linguistic variables, which are changed to fuzzy numbers from input variables in the process of fuzzification. Fuzzy interference is the step, in which the rule base is formed using conditional sentences < If, Then >, and its result is a linguistic variable. The last phase – defuzzification – transforms the results of the fuzzy interference into the real numeric value. Basic assumptions of the fuzzy system were identified by Fullér (1995, 144-145) and we also follow this methodological process:

1. Finding out if the fuzzy system is the right choice for the problem. If the knowledge of the system behaviour is described in an approximate form or by heuristic rules, then fuzzy logic is appropriate. Fuzzy logic can also be useful in understanding and simplifying processing if the system behaviour requires a complex mathematical model.
2. Identification of inputs, outputs and their ranges. The range of the measurement typically corresponds to the range of input variables and the range of control measures provides a range of output variables.
3. Definition of the membership function for each input and output variable. The number of the required membership functions is considered and is depended on the system behaviour.
4. Creation of the rule base (RB), however, it has to be determined how many rules are necessary. The number of rules is determined by the multiplication of attributes of each input variables. Thus, in case of two input variables both having three attributes, the number of rules is 3.3 = 32 = 9.
5. Verification, if input rules give an output in the accepted range and if this output is appropriate and correct according to the rules of the input set.

To provide the calculation and analysis we used the software fuzzyTECH 5.54 for Business and Finance.

4 Results

The application of fuzzy logic in conditions of the behavioural financing followed the problem of the investment policy determined by Bojazdiev and Bojadziev (2007). We focused on the risk aspects of investment decision-making, where the financial risk of a company (investor) was searched in terms of its economic result and total assets (property). The result of the study is the determination of the tolerance of risk on the scale from 0 to 100 in per cents (fuzzy tech uses relative numbers on the scale from 0 to 1 with membership functions), which may help the financial institution to group the investors according to the tolerance of risk and adopt proper investment policy.

To model the financial risk of an investor, we define annual income (*AI*) and property (*P*) as input variables

Table 1: Input and output variables for the fuzzy inference system

Variable	**Values of membership functions**	**Range**
AI	small, medium, high	Small when a variable value is below 20, medium when between 20 and 80 and high when above 80.
P	small, medium, high	
TR	small, medium, high	

and the tolerance of risk (*TR*) as the output variable. These three variables - having the attributes of small, medium and high - may be written as fuzzy sets (Table 1).

The defined variables are fuzzy numbers of universal sets $U_1 = \{x \text{ x } 10^3 \mid 0 \le x \le 100\}$, $U_2 = \{y \text{ x } 10^4 \mid 0 \le y \le 100\}$, $U_3 = \{z \mid 0 \le z \le 100\}$.

Real numbers *x* and *y* represent sums in thousand or ten thousands and *z* is for the risk tolerance which is from the interval [0, 100]. To be able to use the variables *S*, *M* and *H* as fuzzy numbers, their membership functions have to be assigned.

$$\mu_s(v) = \begin{cases} 1 & 0 \le v \le 20 \\ \dfrac{50-v}{30} & 20 \le v \le 50 \end{cases}$$

$$\mu_M(v) = \begin{cases} \dfrac{v-20}{30} & 20 \le v \le 50 \\ \dfrac{80-v}{30} & 50 \le v \le 80 \end{cases} \tag{1}$$

$$\mu_H(v) = \begin{cases} \dfrac{v-50}{30} & 50 \le v \le 80 \\ 1 & 80 \le v \le 100 \end{cases}$$

Each defined input and output variable has to be determined by the membership function. However, an appropriate membership function is very important as it affects a fuzzy interference system. It is a subjective matter of an analyst depending on their knowledge, skills and preferences; thus, we used the triangular and trapezoidal types of functions, following the equation (1), as shown in Figure 2.

The most important step is the formation of the fuzzy rule base; it is necessary to consider the weight and importance of each input criteria. In our model, we work with nine rules, which are schematically portrayed in Figure 3.

Looking at these rules in details, we see that they describe the natural behaviour of people. It is clear, that an investor (a company) with small income and level of total assets is willing to undergo only a small risk when investing their assets. On the contrary, having high annual income and total assets mean that people are more likely to invest with larger risk. Of course, these assumptions do not apply equally to everyone. It is possible to adjust these rules in a case of the risk aversion. However, for the initial categorization of clients without further research, these rules are sufficient.

The last step of the process - when the membership functions of inputs and outputs are set, all IF-THEN rules are defined - is to set the values of the individual attributes, which are of vital importance to determine the final evaluation of the financial decision-making of the individual investor. Fuzzy tech software 5.54 uses the Interactive Debug Mode to determine the output value, thus, we have to set the single values of input attributes and we assess an investor with the annual income of 40,000 € and property of 250,000 €. The main aim of this step, defuzzification, is to change the final function of the outputs to the real (crisp) value. For the calculation of non-fuzzy number in the study, we use the centre of area method, the most popular one with the best accuracy of the results. It means that the centre of the plot area is limited by the final function and the axis; the shape of the function has to be taken into consideration (Dostál, 2012). The following figure (Figure 5) demonstrates the numerical value of the risk tolerance (the resulting value is 9.998) of the client and the resulting membership function. The minimum function for fuzzy inputs creates the relevant strength of rules; the minimum function gives the results in divided triangles and trapezoids; the resulting rule - tolerance of risk is depicted in Figure 4 by a black line.

In the context of the application of the fuzzy logic principles in the financial decision making, we can conclude, that financial risk of a client (company, investor) can be assumed, knowing their annual income and total assets, on the scale from 0 to 100. The study provides a guide based on fuzzy rules, capturing the complex system, where humans are involved. Fuzzy logic is an effective tool of modelling in the environment characterized by uncertainty and imprecision, which definitely is the case of the financial decision-making. The model calculation shows that the client with the annual income of 40,000 € and property of 250,000 € is specified by small risk tolerance. The similar methodology may be used to assess the risk tolerance of any investor, knowing their aversion and tolerance to risk may help the financial institution offer an appropriate investment product and understand the way of individual psychology in investor decision-making, and also to adopt a proper investment strategy (in case of small risk tolerance it is advised to apply the conservative investment strategy).

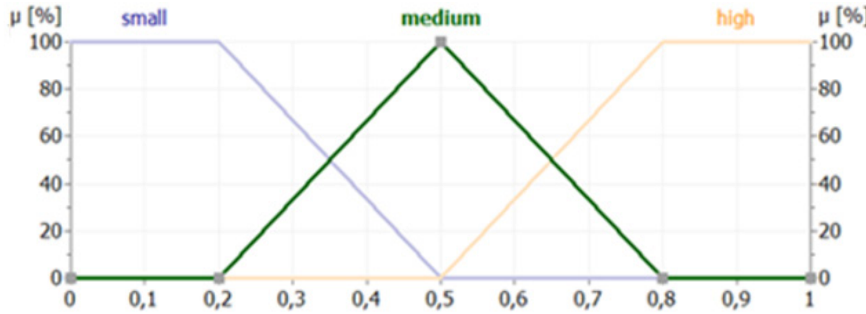

Figure 2: Membership function of input and output variables

	Name	If	And	Operators	Then	With
B1	RB1	1	2	Min / Max	1	
B1.G1		AI	P		TR	DoS [%]
B1.G1.R1		AI.*small*	P.*small*	=>	TR.*small*	100
B1.G1.R2		AI.*small*	P.*medium*	=>	TR.*small*	100
B1.G1.R3		AI.*small*	P.*high*	=>	TR.*medium*	100
B1.G1.R4		AI.*medium*	P.*small*	=>	TR.*small*	100
B1.G1.R5		AI.*medium*	P.*medium*	=>	TR.*medium*	100
B1.G1.R6		AI.*medium*	P.*high*	=>	TR.*high*	100
B1.G1.R7		AI.*high*	P.*small*	=>	TR.*medium*	100
B1.G1.R8		AI.*high*	P.*medium*	=>	TR.*high*	100
B1.G1.R9		AI.*high*	P.*high*	=>	TR.*high*	100

Figure 3: Fuzzy rule base for tolerance of risk

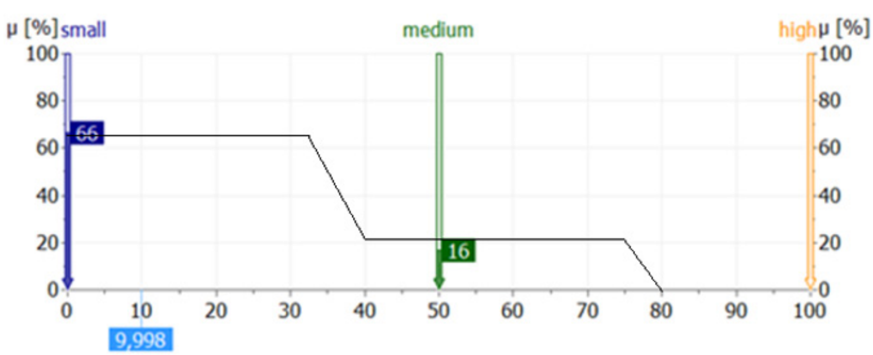

Figure 4: Defuzzification

5 Discussion, conclusions and recommendations

Behavioural finance proposes psychology-based theories to explain stock market anomalies, such as severe rises or falls in stock price (Ritter, 2003). The purpose is to identify and understand why investors make certain financial choices. Within behavioural finance, it is assumed the information structure and the characteristics of market participants systematically influence individuals' investment decisions as well as market outcomes. Financial decision-making accepting behavioural principles learn the investors make effective decisions to maximize profitability and achieve strategic organizational goals. Thus, behavioural finance introduces psychology, sociology and other research methods into the study of investment behaviour to explain how investors handle the information and take actions. As their reactions do not follow the traditional principles of decision-making, we try to explain them using fuzzy sets, mathematical sets with the property that an object can be a member of the set, not a member of the set, or any of a continuum of states of being a partial member of the set (Zadeh, 1968).

The research of Yu and Zheng (2015) shows, investors do not always adopt rational behaviour as the traditional finance theory assumed but make many irrational decisions based on individual cognitive and prejudices. In addition, the fact that the traditional model cannot explain the complexity of financial market movements makes the field of behavioural finance boom (Bianchi et al., 2015). Some authors even indicate the shift from behavioural finance to social finance, which studies the structure of social interactions, how financial ideas spread and evolve and how social processes affect financial outcomes (Hirshleifer, 2015).

The empirical contribution of the research is reflected in the introduction and deepening the knowledge of the fuzzy logic usage in financial decision- making. The basic advantage of fuzzy logic is the ability to express mathematically information, which is originally expressed in a verbal form. This makes fuzzy logic a good tool for working with behavioural data. Behavioural finance takes the human factor in making financial decisions into account. For this reason, behavioural finance often uses linguistic data, so fuzzy logic-based methods are appropriate for their description. The strong connection between fuzzy sets theory and behavioural finance theory was proved in the research of Aguiar and Sales (2011).

Behavioural finance, however, is not the only area of finance where fuzzy logic can be used. The fuzzy logic method, described in this paper, can be applied to various financial problems. We use the method to find out the level of the risk tolerance of clients and investor based on their annual income and total assets. We presented the manual calculation of the membership function, using the model scenario, as well as the software application. The results can be easily applied for the database of clients of the chosen financial institution, which can help offer an appropriate investment product for a group of customers with the same level of the risk tolerance. Moreover, the knowledge of risk tolerance is an important measure of the financial decision-making process. As the information about the financial institutions´ client is very sensitive and legislatively protected, we did not get reliable data to verify the model. The limitation of the study comes from the fact, that the study is based on two input variables (annual income and total assets) and other linguistic determinants were not considered. For further research, we suggest to include more qualitative (linguistic) variables into the fuzzy logic process, which may improve the behavioural perception focused on the risk aspects of investment decision-making. An inspiration can be found in the recently published researches focused on hesitant fuzzy sets and methods applied in the decision-making process by Torra (2010), Zhang and Xu (2017), Liao and Xu (2017) or Ayhan (2018).

The paper proves that despite the fact, that fuzzy logic is currently used mainly in technical directions, it is applicable also in financial management. We determine a strong link between fuzzy logic and behavioural finance. This study can be perceived as a stimulus for further research into the use of fuzzy logic in finance, financial management and decision-making. Especially in cases where it is necessary to consider the influence of human and the occurrence of linguistic variables.

Fuzzy sets can accurately model the human decision-making process; their using in modelling behaviour when precision is not necessary is legendary. Behavioural psychology has shown that the fuzzy logic model of human decision-making has validity in the real world.

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