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A DECISION-MAKING MODEL FOR EXPLAINING DRIVER BEHAVIOR

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Marjana Čubranić-Dobrodolac

Title

A Decision-Making Model for Explaining Driver Behavior

Annotation

The main topic of this dissertation is the modeling of driver behavior based on an examination of their psychological traits. After a detailed review of relevant literature, five questionnaires have been prepared to collect the data. Four questionnaires are related to testing the psychological constructs of drivers and an additional one is a demographical and driving history questionnaire. A survey was carried out at the sample of 305 drivers, from which there were 202 professional drivers and 103 drivers of privately owned vehicles. The data were processed by two general approaches: statistical and fuzzy logic. The implemented statistical methods are hierarchical regression analysis and binary logistic regression. The driver behavior is modeled by fuzzy inference systems where the inputs are the results from psychological tests and the output is the number of experienced road traffic accidents in driving history. The performance of a fuzzy inference system that can be considered as a decision-making tool for explaining driver behavior, is further enhanced, in the sense of adjusting its results to the empirical data, by applying the bee colony optimization metaheuristic. Based on the obtained results, adequate recommendations for traffic safety improvement are proposed.

Keywords

psychological traits, driver behavior, traffic accidents, hierarchical regression analysis, binary logistic regression, fuzzy inference system, bee colony optimization

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List of Abbreviations

ABC	-	Artificial Bee Colony
ACO	-	Ant Colony Optimization
ADBQ	-	Aggressive Driving Behavior Questionnaire
AFA	-	Advanced Firefly Algorithm
ANFIS	-	Adaptive Neuro-Fuzzy Inference System
BSA	-	Bats Sonar Algorithm
BCO	-	Bee Colony Optimization
BIS-11	-	Barratt Impulsiveness Scale
DAQ	-	Manchester Driver Attitude Questionnaire
DE	-	Differential Evolution
DS	-	Direct Search
EC	-	European Commission
EU	-	European Union
FIS	-	Fuzzy Inference System
GA	-	Genetic Algorithms
GWO	-	Grey Wolf Optimizer
HS	-	Harmony Search
IANN-PSO	-	Improved Artificial Neural Network-Based Particle Swarm Optimization
IWO	-	Invasive Weed Optimization
MF	-	Membership function
MVO	-	Multi-Verse Optimizer
NHTSA	-	National Highway Traffic Safety Administration, USA
NSGA-II	-	Nondominated Sorting Genetic Algorithm-II
PID	-	Proportional-Integral-Derivative
PSO	-	Particle Swarm Optimization
QLSA	-	Quantum-inspired Lightning Search Algorithm
RTAs	-	Road Traffic Accidents
SD	-	Standard Deviation
TS	-	Takagi–Sugeno
USA	-	United States of America
WHO	-	World Health Organization
WM	-	Wang and Mendel

1 Introduction

The Global Status Report on Road Safety 2018 (WHO, 2018) reveals that in 2016, approximately 3700 people died in road traffic accidents (RTAs) per day in the world, and tens of millions of people are injured or disabled every year. Although the knowledge about RTAs is increasing, there are still many lives lost on the roads. This is evident even in the most developed countries. For example, more than 90 people die in the RTAs in the USA every day (NHTSA, 2019), or more than 70 in the European Union (EC, 2019).

Based on data obtained from the World Health Organization (WHO, 2018), there is a general trend of an increase in the absolute number of deaths on the roads during the time. In the year 2000, there were 1.15 million lives lost in RTAs globally, while in 2016, this number was increased to 1.35 million. However, the rate of death relative to the size of the world's population is considered approximately constant. The rate of deaths, which is calculated as the number of deaths per 100,000 inhabitants, was 18.8 in the year 2000. The same parameter was slightly reduced to 18.2 sixteen years later. Having in mind the population growth and rapid motorization that has taken place over the considered period, this implies that certain progress is achieved in the field of traffic safety. However, the mentioned data are still worrisome and far from the targets set by competent institutions. For example, the United Nations General Assembly adopted a series of sustainable development goals in September 2015. One of these goals related to road safety implies a target to halve the number of global deaths and injuries from RTAs by 2020. It is already obvious that this target will not be met. An illustrative data that reveals how serious the problem of RTAs is, can be found in the fact that RTAs injuries are the eighth cause of death for all age groups, while they are the leading cause of death for children and young adults aged 5–29 years.

To develop as efficient as possible programs in the field of traffic safety, the policymakers permanently need to analyze the causes of accidents and to understand as good as possible the concept of driver behavior. There are three general categories of causes of RTA occurrence: the vehicle, road, and human factor. It is generally accepted in the literature that the human factor is the far most common cause of RTAs. Therefore, it is a need to investigate the driver behavior with the aim to conclude what kind of human activities lead to the increased likelihood of RTA occurrence. Furthermore, the studies are confirming that the human activities that lead to the RTAs are induced by certain psychological traits of a driver.

The main goal of this dissertation is to propose a methodology for modeling driver behavior based on the investigation of current methods of explaining driver behavior. This modeling would be based on assessing the propensity for RTAs by knowing the personality traits of a driver. To achieve this, it is necessary to examine which psychological instruments should be used for assessing the personality traits of a driver and what are the adequate research methods that can be applied for this purpose.

Consequently, in this dissertation, the data are collected by four questionnaires related to psychological constructs of drivers and one general questionnaire concerning demographic issues and driving history. The survey is carried out covering a sample of 305 drivers of different age groups, including both professional and the drivers of privately owned vehicles.

To analyze the data, two general approaches are applied. The first relates to statistics and the second to fuzzy logic. On one hand, to determine the relationships between the variables of interest, the hierarchical regression analysis and binary logistic regression are implemented. On the other hand, the modeling of driver behavior is performed by testing various Fuzzy Inference Systems (FISs) and after the most convenient type is determined, its optimization is done by the proposed bee colony optimization algorithm. The final FIS which describes the empirical data in a best-found way can be used as a decision-making tool for explaining driver behavior. An implementation of the proposed decision-making tool may have significant positive implications in the field of traffic safety, saving the lives of people and bringing to significant cost savings.

2 Overview of the current knowledge

In this section, an overview of existing knowledge in the field of the dissertation is given. The literature review is structured into four parts. The first part relates to the investigation of causes of RTAs, then to the research about the human factor in the occurrence of RTAs and to research concerning methods for measuring the human factor. Further, the literature is investigated about the possible methods of processing the collected data. There are two general approaches implemented in the literature for this purpose. One direction is about the statistical methods to find the relationship between the variables of interest. The other concerns the implementation of fuzzy logic to examine the mentioned relationship and to form a decision-making model for explaining driver behavior. The final part is about the optimization algorithms for adjusting the proposed FIS to the empirical data.

2.1 A review of literature about the causes of accidents, human factor and instruments that can explain driver behavior

Each RTA is unique with many particular circumstances; however, some general causes can be classified into three general groups (Wangdi, Gurung, Duba, Wilkinson, Tun & Tripathy, 2018): human factors, mechanical factors related to the vehicle, and environmental factors and road conditions.

A notable study that considers the vehicle factor is by Vranjes, Vasiljevic, Jovanov, Radovanovic, and Duric (2019) where the research was carried out to investigate how certain vehicle malfunctions affect the road safety. Based on data for the period from 1997 to 2014, they concluded that the technical malfunction of vehicles as a cause for accident occurrence has a share of just 0.72 % in the total number of RTAs.

When it comes to the road characteristics as a cause of accidents, it may also be stated that this factor rarely contributes to the occurrence of accidents. For example, Rudny and Sallmann (1996) critically analyzed the actual physical evidence of accidents involving alleged road defects. However, the severity of road accidents can be strongly correlated with hazardous weather conditions, such as fog, snow, heavy rainfall, and storms (Lee, Chae, Yoon, and Yang, 2018). Certain conclusions about road safety can be obtained by analyzing the road characteristics and Shah and Ahmad (2019) proposed a methodology for identification of risky segments of a motorway considering the road infrastructure and traffic stream characteristics.

By analyzing the literature, it can be noticed that the influence of road factors on RTAs can be considered as very complex because it often appears in various forms, but only in rare occasions considering the total number of RTAs. However, the road infrastructure should be designed and constructed in such a way to reduce the technical risk of RTAs.

The most significant ways of the road characteristics influence the RTAs are reflected in the fact that it impacts other factors, such as the driver and the vehicle, affects the severity of the consequences of RTAs, and at the same time determines the conditions of traffic flow. For example, the road is a direct cause of RTAs in cases when there is a sudden change in the road characteristics due to the existence of a very sharp road curve, and when such a curve is invisible to the driver until the last moment of entering it. In these circumstances, there is a possibility that the driver can not react on time and adjust the speed. The initiatives to enable the design of roads of optimal safety forced the development of the science of transport and traffic engineering.

The research results from Pesic, Markovic, Vujanic, and Rosic (2012) show that the road factor is the cause of 3% of RTAs. Even though this is a relatively low percentage, the improvement actions are welcome in this field, and Gichaga (2017) mentions the following as some of the most important:

- Road geometric design should avoid black spots, i.e. dangerous places on the road, wherever possible.
- Road design should address the various elements that contribute to over-speeding through measures such as traffic signs, road markings, etc.

In the literature, it is generally accepted that human factors have the biggest and most frequent impact on the occurrence of traffic accidents. For example, based on European Union research (EU, 2019), 95 % of all traffic accidents on Europe's roads involve human error. Similarly, Sam, Velanganni, and Evangelin (2016) reports that human errors are recognized as the far most common influential factor causing more than 90 % of RTAs. This factor may be analyzed in various segments, such as fatigue, inattention, impairment from drugs or alcohol, risky maneuvers, violation of traffic rules, etc. Duan, Xu, Ru, and Li (2019) classified and quantified driving fatigue according to the driving fatigue degree.

The authors determined three levels of driving fatigues: mild, moderate, and severe fatigues, by measuring the variations in a heartbeat using an electrocardiogram. Further, they concluded that drivers become fatigued within a significantly shorter time while driving in the high-altitude area. Dehzangi, Sahu, Taherisadr, and Galster (2018) proposed a monitoring system to assess the level of driver distraction, which occurs as a result of different non-driving related activities such as communicating with passengers, phone use, eating and drinking. Distracted driving is a particularly present factor in the population of young drivers (Zhang, Mehrotra, & Roberts, 2019). Li and Chang (2019) used the geographic information system to collect traffic accidents data and concluded that the most frequent cause of accidents were: illegal overtaking, road races, lane change, improper driving direction, drunk driving, and not maintaining a safe distance. Further, operating a vehicle while impaired by alcohol or drugs is a serious offense that can lead to the occurrence of RTAs. By analyzing the police reports about 17,945 tested drivers in urban areas and 19,507 in rural areas, Pesic, Antic, Smailovic, and Markovic (2019) concluded that the motorcyclists represent a category with the highest share of driving under the influence.

It is proven that the drivers who do not respect the traffic rules in one segment, usually do not behave properly also in some other segment. For example, the drivers in Serbia are forbidden to talk on the phone while driving, except when using a hands-free device. A study by Čubranić-Dobrodolac, Čičević, Dobrodolac, and Nešić (2013) showed that the participants who violate this rule, are prone to drive under the influence alcohol as well, especially the group of drivers who experienced more than three RTAs in their driving experience. This points to the conclusion that the human factor as a cause of RTAs and general driver behavior can be explained to a large extent by the corresponding psychological traits, as confirmed by Elander, West, and French (1993), Furnham, and Saipe (1993), Ulleberg, and Rundmo (2003), Shinar, (2007), Sârbescu, and Maricuţoiu (2019) or Zheng, Ma, and Cheng (2019). Accordingly, there is a need to investigate which psychological traits can indicate an accident-prone driver, and how to identify them to prevent or reduce the number of RTAs and their consequences.

There are many instruments for the assessment of psychological traits that can explain driver behavior. By reviewing the literature, it can be concluded that there are two most common psychological traits considered as the most important indicators of drivers who are characterized by risky behavior in traffic and who are prone to participate in RTAs: aggressiveness and impulsiveness (Jonah, Thiessen, & Au-Yeung, 2001; Dahlen, Martin, Ragan, & Kuhlman, 2005).

Reports of aggression in the context of driving cite different forms of behavior in traffic that range from flashing lights, honking, verbal threats to other traffic participants, gestures, incapacity to maintain the proper distances from other vehicles, blocking and cutting the road to other vehicles up to more pronounced forms of aggressive behavior, such as car-ramming or even physical attacks on other drivers (Özkan, Lajunen, Parker, Sümer, & Summala, 2010). In the report of AAA Foundation for Traffic Safety (FTS, 2009), aggressive driving behavior has been identified as the basic cause of 56 % of accidents with fatalities occurred in the USA between 2003 and 2007. When it comes to the impulsiveness, there are different definitions in the literature. In the broadest sense, impulsiveness is defined as a tendency to react quickly and unexpectedly, without thinking about the negative consequences of such a response or alternative reactions (Plutchik and van Praag, 1995; Moeller, Barratt, Dougherty, Schmitz, & Swann, 2001). Despite the apparent conceptual overlap and close relationship between the considered two psychological traits, in terms of poor appraisal of behavioral outcomes during decision-making, as well as insufficient self-control, they should not be equated, whereas aggressive behavior, as opposed to impulsive, includes the intent to harm the other person. In the following text, two psychological instruments will be more detailed explained, and further, the overview of their use in the literature is offered. The psychological instrument more related to the aggressiveness is the Aggressive Driving Behavior Questionnaire (ADBQ). On the other hand, the instrument for measuring impulsiveness is the Barratt Impulsiveness Scale (BIS-11).

The ADBQ was designed by Mouloua, Brill, and Shirkey (2007). The authors intended to create an instrument with good predictive power considering aggressive situations that are typical in driving. These vary from gestures directed toward other drivers to explicit aggressive outbursts, such as passing through a red light at an intersection. The instrument contains 20 questions. The respondents were asked to assess the likelihood of manifestation of aggressive driving using a 6-point Likert scale. Results were given in the range of 1 = never to 6 = almost always. Based on the answers, a score from the ADBQ could range from 20x1=20 to 20x6=120.

The BIS-11 instrument is used for the assessment of impulsivity while driving. In this thesis, a version of BIS-11 constructed by Patton, Stanford, and Barratt (1995) will be implemented. The questionnaire consists of 30 questions, which cover a variety of situations and aspects characteristic of impulsive behavior. The respondents were required to estimate, using a 4-point Likert scale, the extent to which they agree with the statements that describe the most representative impulsive habits and practices. The scaled responses correspond to the following statements: from 1 = never/rarely to 4 = always/almost always. The score obtained from this instrument can vary from 30 to 120.

When speaking about the previously explained psychological traits - aggressiveness and impulsiveness, it should be noticed that they are mostly considered as innate traits. On the other hand, in the literature, there are also psychological instruments for explaining driver behavior that measure the traits acquired during life. These relate to the attitudes of drivers and their self-assessment (Iversen, & Rundmo 2004; Al-Rukaibi, Ali, & Aljassar, 2006; Sundström, 2008; Jain, Calvert, Clayton, & Parkhust, 2017). An example of the instrument that measures attitudes is the Manchester Driver Attitude Questionnaire (DAQ). The Questionnaire for Self-Assessment of Driving Ability measures the mentioned self-assessment of drivers.

The Manchester DAQ is a questionnaire for the assessment of attitudes toward risk propensity while driving, constructed by Parker, Lajunen, and Stradling (1998). The questionnaire consists of 20 questions with a Likert scale of answers from 1 = strongly disagree to 5 = strongly agree. Most questions refer to the typical traffic situations that can be characterized as high-risk. The DAQ includes statements relating to speeding, drink-driving, close-following, and dangerous overtaking. Here the scores are arranged in such a way that higher scores correspond to higher risk propensity while driving. Scores of subjects could range from 20 to 100 points.

The Questionnaire for Self-assessment of Driving Ability was developed by Tronsmoen (2008). It consists of a set of statements about how drivers react in certain traffic situations. Based on the responses, it is possible to obtain information about participants' self-perception as a driver. There are 22 questions and answers in the form of a 4-point Likert scale. Answers ranged from 1 = never, to 4 = always/almost always. A higher score on the test corresponds to a better evaluation of one's driving abilities.

Depending on the concrete questionnaire, they are used more or less in the literature. There are several examples of ADBQ use. This is presented in Table 1. The authors mainly implemented this instrument at the sample of university students that are holders of valid driving licenses. In the following tables which describe the use of considered psychological instruments, there is also information about the Mean and Standard deviation (SD) values from the samples of other authors. Finally, there is also a value of Total mean explaining the mean value of all samples from the literature. By knowing these values, it is possible to compare the results from this dissertation considering the obtained scores from used instruments with the results of other studies.

Tab. 1 The use of ADBQ in the literature (Source: Author)

Source (Authors and year)	**Type of sample**	**Number of participants in the sample**	**Mean**	**SD**
Brill, Mouloua, & Shirkey (2009)	Students	29	-	-
Brill, & Mouloua (2011)	Students	495	51.37	-
Gurda (2012)	Students	285	55.21	12.43
Total mean			**53.29**	

The BIS-11 is much more frequently used and more data about its implementation are given in Table 2. The data in the table are structured as previously explained, by offering the information about the type of sample in the study, number of participants, mean and SD value.

Tab. 2 The use of BIS-11 in the literature (Source: Author)

Source (Authors and year)	**Type of sample**	**Number of participants in the sample**	**Mean**	**SD**
Patton, Stanford, & Barratt (1995)	Students, Patients (including addicts), prisoners	412 248 73	64.94 69 76.30	10.17 10.28 12.61
Li, & Chen (2007)	Adolescents	682	72.5	8.7
Von Diemen, Szobot, Kessler, Pechansky (2007).	Adolescents	464	62.2	11.6

Source (Authors and year)	Type of sample	Number of participants in the sample	Mean	SD
Antonini, Siri, Santangelo, Cilia, Poletti, Canesi, Caporali, Mancini, Pezzoli, Ceravolo, Bonuccelli, & Barone (2011)	Patients	103	63.7	9.5
Kam, Dominelli, & Carlson (2012)	Students	85	63.04	9.29
Lu, Jia, Xu, Dai, & Qin (2012)	Patients	200	62.45	16.87
Reise, Moore, Sabb, Brown, & London (2013)	Adolescents	691	59.18	9.54
Steinberg, Sharp, Stanford, & Tharp (2013)	Students	1178	-	-
Smulders, Esselink, Cools, & Bloem, (2014)	Patients	315	59.5	-
Rot, Moskowitz, & Young (2015)	Healthy working individuals	48	62.68	7.33
Martínez-Loredo, Fernández-Hermida, Fernández-Artamendi, Carballo, & García-Rodríguez (2015)	Students	1183	60.69	11.40
Lyvers, Basch, Duff, & Edwards (2015)	Students	70	66.43	9.79
Dudek, Siwek, Jaeschke, Drozdowicz, Styczeń, Arciszewska, Chrobak, & Rybakowski (2016)	Extreme athletes	715	61.4 59.0	10.0 9.4
Herrera-Diaz, Mendoza-Quiñones, Melie-Garcia, Martínez-Montes, Sanabria-Diaz, Romero-Quintana, Salazar-Guerra, Carballoso-Acosta, & Caballero-Moreno (2016)	Female alcohol addicts	25	59.19	8.3
Marczinski, Hertzenberg, Goddard, Maloney, Stamates, & O'Connor (2016)	Students	146	55.05 53.64	7.40 8.62
Jakubczyk, Brower, Kopera, Krasowska, Michalska, Loczewska, Majewska, Ilgen, Fudalej, & Wojnar, (2016)	Alcohol addicts	336	69.79	10.48

Source (Authors and year)	Type of sample	Number of participants in the sample	Mean	SD
Zhu, Cortes, Mathur, Tomasi, & Momenan (2017)	Alcohol addicts	51	67.0 52.1	14.8 8.2
Canan, Karaca, Düzgün, Erdem, Karaçaylı, Topan, Lee, Zhai, Kuloğlu, & Potenza (2017)	Students	652	58.1 59.3	13.00 11.8
Moustafa, Tindle, Frydecka, & Misiak (2017)	Volunteers	141	59.63	19.27
Reist, Mee, Fujimoto, Rajani, Bunney, & Bunney (2017)	Patients	57	74.12	12.40
Tang, Zhang, Yan, & Qu (2017)	Students	125	69.76 67.57 63.56	8.00 6.84 7.70
Lindstrøm, Wyller, Halvorsen, Hartberg, & Lundqvist (2017)	Patients	110	59.37	7.89
Total mean			**63.14**	

Tab. 3 The use of DAQ in the literature (Source: Author)

Source (Authors and year)	Type of sample	Number of participants in the sample	Mean	SD
Rowland, Davey, Freeman, & Wishart (2007)	Taxi drivers	182	-	-
Gordon (2007)	Adolescents	25	62.67	7.23
	Young Adults	8	59.00	7.98
	Older Adults	17	64.24	9.44
Davey, Freeman, & Wishart (2007)	Drivers	443	-	-
Van Vuuren (2012)	Young drivers	81	48.95 53.95	7.76 9.76
Kinnear, Helman, Wallbank, & Grayson (2015)	Drivers	183	-	-
Starkey, & Isler (2016)	Young drivers	46	57.41	8.72
	Adult drivers	32	53.91	9.22
Total mean			**57.16**	

Since the DAQ and the Questionnaire for Self-assessment of Driving Ability are the instruments more concrete related to driver behavior, the examples found in the literature consider the sample of drivers. These examples are shown in Tables 3 and 4.

By reviewing the literature, there is no example of research that examines the impact of all four considered instruments together for explaining driver behavior and for the design of a model for assessing driver propensity for RTAs. Accordingly, this was a motive to carry out this type of research in this dissertation.

Tab. 4 The use of the Questionnaire for Self-assessment of Driving Ability in the literature (Source: Author)

Source (Authors and year)	Type of sample	Number of participants in the sample	Mean	SD
Tronsmoen (2010)	Young drivers	1419	-	-
Jovanovic, Stanojevic, & Jaksic (2014)	Drivers	225	-	-
Van Vuuren (2012)	Young drivers	50	73.18	11.23
			75.93	10.09
Total mean			**74.55**	

2.2 A review of literature about the use of hierarchical regression analysis and binary logistic regression to examine a relationship between the variables of interest

To assess a relationship between the variables of interest by a statistical method, the hierarchical linear regression is very popular in the literature. The implementation of this technique implies a design of several models called "blocks" by adding the variables gradually. A purpose is to examine whether adding variables significantly improves a model's ability to predict the criterion variable, in this case, the involvement in RTAs.

The hierarchical regression analysis is widely used in the literature. Several examples of its implementation in the field of driver behavior are offered in Table 5.

Tab. 5 The use of the hierarchical regression analysis in the literature in the field of driver behavior (Source: Author)

Source (Authors and year)	Predictors	Criterion variables
Swann, Lennon, & Cleary (2017)	Driving moral disengagement, driving anger	Driving aggression
Buckley, Kaye, & Pradhan (2018)	Attitude toward the behavior, subjective norms, and perceived behavioral control	Intentions to use automated vehicles
Yang, Liu, Su, Cherry, Liu, & Li (2018)	Attitude and perceived behavioral control, moral norm and self-identity	Red-light running
Antoniazzi, & Klein (2019)	Sensation seeking, and aggression	Errors, speeding, stunts, protective gear use
Erkus, & Ozkan (2019)	Safety skills and perceptual motor skills	Young male drivers' speeds, overtaking behaviors, and behaviors at traffic lights

Swann, Lennon, and Cleary (2017) introduced the Driving Moral Disengagement Scale (DMDS) to examine if a moral disengagement can be a predictor of aggressive driving. The drivers who achieved high scores on driving moral disengagement were significantly more likely to report aggressive responses to driving situations than those with low driving moral disengagement scores. By their implementation of hierarchical regression, the results show that driving moral disengagement significantly predict driving aggression, being a more useful predictor than driving anger. Buckley, Kaye, and Pradhan (2018) used the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM) to assess drivers' intended use of automated vehicles. A hierarchical regression analysis revealed that the attitudes, subjective norms, and perceived behavioral control, were significant predictors of intentions to use automated vehicles. The paper of Yang, Liu, Su, Cherry, Liu, and Li (2018) investigate the psychological motivation for e-bike drivers for red-light running, which represents an action characterized by a high level of risk in traffic. The results of hierarchical regression showed that attitude and perceived behavioral control, moral norm and self-identity are significant predictors for the intention of red-light running behavior. Antoniazzi, and Klein (2019) collected the data from 550 motorcyclists and by using hierarchical regression concluded that sensation seeking and aggression are strongly associated with driver behavior, such as riding errors, speeding, etc. Erkus, & Ozkan (2019) used the hierarchical regression on the sample of 38 male taxi drivers and 40 male private car users and concluded that safety skills are in opposite associations with young male drivers' speeds, overtaking behaviors, and their behaviors at traffic lights.

Tab. 6 The use of the binary logistic regression in the literature in the field of driver behavior (Source: Author)

Source (Authors and year)	Independent variables	Dependent variables
Hussain, & Shi (2019)	Driving without driving licenses	Involvement in RTAs
Duy, Nguyen, De Gruyter, Su, & Nguyen (2019)	Low education levels, high daily travel distances, regular smoking, and using a mobile phone while driving	Involvement in RTAs
Cheng, Zu, Lu, & Li (2019)	Blood alcohol concentration	Involvement in RTAs
Farah, Piccinini, Itoh, & Dozza (2019)	Driving speed	Overtaking strategy (flying or accelerative)
Hill, Sullman, & Stephens (2019)	Drivers' behavioral, normative and control beliefs	Using a mobile phone while driving

In the case when the dependent variable is binary in nature or it is presented in this way, a simple linear regression is not useful; however, we can use binary logistic regression. The purpose of binary logistic regression implementation is to predict the relationship between predictors or independent variables and a predicted variable or dependent variable. It should be noted that in this case, the dependent variable is binary, which means that that it can take one of two values.

Binary logistic regression is widely used in the literature. Some cases where this statistical technique is implemented in the field of driver behavior are presented in Table 6.

Hussain and Shi (2019) examined the effects of driving without prior driving training and without driving licenses on traffic safety. They implemented the binary logistic regression and concluded that this type of violation is a significant factor that influences RTAs involvement. Duy, Nguyen, De Gruyter, Su, and Nguyen (2019) carried out a survey with 602 motorcycle taxi riders to examine the influencing factors on the occurrence of RTAs.

The binary logistic regression showed that RTAs were associated with low education levels, high daily travel distances, regular smoking, and using a mobile phone while driving. Cheng, Zu, Lu, and Li (2019) investigating a relationship between intoxicated driving factors and involvement in RTAs. The binary logistic regression analysis was performed at the sample of 1010 drivers confirming that blood alcohol concentration affects the likelihood of being involved in RTAs. Farah, Piccinini, Itoh, and Dozza (2019) examined one of the crucial phenomena in traffic safety and driver behavior – overtaking. By using the binary logistic regression, they found a relationship between driving speed and overtaking strategy (flying or accelerative). The flying overtake is preferable from many standpoints, besides safety issues, it is also environmentally friendly because of lower speed variations. Hill, Sullman, and Stephens (2019) demonstrated by the binary logistic regression that higher scores at the Mobile Phone Involvement Questionnaire, which covers drivers' behavioral, normative and control beliefs, is significantly associated with mobile phone use while driving.

2.3 A review of literature about the use of fuzzy logic in the field of driver behavior

Fuzzy logic is widely used in the field of road transportation. Ivanov (2015) offers a review of fuzzy methods in automotive engineering applications where the following domains are differentiated: vehicle dynamic control systems, driver and driving environment identification, ride comfort control, and energy management of electric vehicles. The field of interest for this dissertation relates to modeling driver behavior. This field is of particular relevance for fuzzy applications because psychological and emotional parameters generally imply a certain level of imprecision and fuzziness.

By reviewing the literature, it is possible to segment the implementation of fuzzy logic to model driver behavior in the following areas:

- Examination of the interaction between the driver and road infrastructure;
- Examination of the interaction between the driver and in-vehicle systems;
- Testing the psychophysical characteristics of drivers;
- Determining a driving style.

An example of modeling the interaction between the driver and road infrastructure using fuzzy logic can be found in the study by Lee and Donnell (2007), where a preference is determined for particular types of road markings most suitable during night-time driving. On the other hand, Sentouh, Nguyen, Rath, Floris, and Popieul (2019) analyzed the interaction between the driver and the in-vehicle system and proposed a steering controller for keeping in the lane, based on the integrated driver-vehicle model using the Takagi-Sugeno control technique.

With regard to the psychophysical characteristics of drivers, Boyraz, Acar, and Kerr (2008) designed a FIS to predict the drowsiness level of the driver. The selected signals for analyses included the level of eye closure, gaze vector, head motion, steering wheel angle, vehicle speed, and force applied to the steering wheel by the driver. Similar research was carried out by Wu and Chen (2008), who analyzed the facial images of drivers and proposed a fuzzy system to warn the driver of drowsiness. Riaz, Khadim, Rauf, Ahmad, Jabbar, and Chaudhry (2018) applied the fuzzy sets to compute the distraction of the drivers and proposed a corresponding road safety system.

Lin, Tsai, and Ko (2013) used fuzzy logic as a method for the early detection of motion sickness. These types of distractions while driving can endanger safety because of a decline in a person's ability to maintain self-control.

Fazio, Santamaria, De Rango, Tropea, and Serianni (2016) used fuzzy logic to identify a particular driving style and to model driving behavior. However, their conclusions about driving style were based on the car velocity and acceleration measurement using on-board diagnostics in the vehicle. Similar research with the same input parameters and on-line collection of data was previously proposed by Dorr, Grabengiesser, and Gauterin (2014). Saleh, Aljaafreh, and Albdour (2013) proposed a fuzzy system to classify driving styles in terms of vehicle-human interactions. They used three input variables: acceleration, speed, and distance between the preceding and host car.

Aggressiveness in driving, although a psychological category may be assessed by explicit parameters of vehicle movement, for example by analyzing driving performance. An example of this is demonstrated in the paper by Aljaafreh, Alshabatat, and Najim Al-Din (2012). The authors measured aggressiveness based on the Euclidean norm of lateral and longitudinal acceleration, as well as considering car velocity.

The fuzzy logic was used also to form an accident prediction model based on input parameters which relate to the road infrastructure, such as road width, pavement conditions, average hourly traffic volume, speed, the number of access points to the highway and traffic signs conditions (Wahaballa, Diab, Gaber, & Othman, 2017; Gaber, Wahaballa, Othman, & Diab, 2017). Selvi (2009) establishes a similar prediction model based on fuzzy logic through factors such as traffic volume, rain status, and the geometry of the roads.

Tab. 7 The use of fuzzy logic in the literature in the field of driver behavior (Source: Author)

Source (Authors and year)	The purpose of the fuzzy inference system
Lee, & Donnell (2007)	Preference for particular types of road markings
Boyraz, Acar, & Kerr (2008)	Detection of drowsiness
Wu, & Chen (2008)	Detection of drowsiness
Selvi (2009)	Accident prediction
Aljaafreh, Alshabatat, & Najim Al-Din (2012)	Assessment of aggressiveness
Saleh, Aljaafreh, & Albdour (2013)	Identification of driving style
Lin, Tsai, & Ko (2013)	Detection of motion sickness
Dorr, Grabengiesser, & Gauterin (2014)	Identification of driving style
Fazio, Santamaria, De Rango, Tropea, & Serianni (2016)	Identification of driving style
Wahaballa, Diab, Gaber, & Othman, (2017)	Accident prediction
Gaber, Wahaballa, Othman, & Diab, (2017)	Accident prediction
Riaz, Khadim, Rauf, Ahmad, Jabbar, & Chaudhry (2018)	Computation of driver distraction
Sentouh, Nguyen, Rath, Floris, & Popieul (2019)	Controller for keeping in lane

All the previously explained research papers are presented in Table 7. The main difference between these studies and the current dissertation is in the type of indicators used for the assessment of driver behavior. In the mentioned studies, the applied indicators can be explicitly measured by certain technical devices. Conversely, the subjective indicators will be used here such as assessment of personality and attitudes related to driver behavior.

2.4 A review of literature about the use of Bee Colony Optimization (BCO) metaheuristic in the field of FIS optimization

The optimization of FIS represents a tuning of the characteristics of FIS to minimize or maximize the objective function, depending on a type of the considered task. Here it is mostly the minimization task because the performance of FIS is generally measured as the level of deviation from certain empirical data. There are numerous examples where this procedure is useful. In the case of the current research, it is used to design as good as possible decision-making tool.

Many papers deal with FIS optimization issues. Therefore, here it will be offered just a review of the most frequently used techniques in the field in the last two years, from 2019 to 2020, which is shown in Table 8. An interesting fact to notice here is that general principles of FIS optimization set up in the past are valid also nowadays and the changes are in terms of newly applied optimizations methods, which have been proposed in the meanwhile. Guillaume (2001) systemized the procedures for fuzzy rule generations from empirical data and structured the optimization methods as “shared partitions”, “clustering”, and “hybrid methods”. The hybrid methods were based on the implementation of neuro-fuzzy modeling or heuristic algorithms, mentioning Genetic Algorithms (GA) as the most popular at that time.

One direction in the optimization procedures is related to the implementation of an adaptive neuro-fuzzy inference system – ANFIS (Jang, 1993). Certain authors combine the ANFIS method with other metaheuristics. Nath, Mthethwa, & Saha (2020) combined particle swarm optimization (PSO) with ANFIS to optimize the rainfall-runoff relationship. Chouksey, Awasthi, & Singh (2020) applied an improved artificial neural network-based particle swarm optimization (IANN-PSO) method to maximize the power from the solar power system.

A development of metaheuristic approaches based on mimicking of behavioral patterns observed in nature has been very popular in recent decades. These techniques were successfully implemented in many cases for solving complex computational tasks, such as optimization of FIS (Castillo, & Melin, 2012).

As previously mentioned, genetic algorithms (GA) are frequently used. Nagammai, Latha, & Varatharajan (2020) used GA to tune the membership functions of FIS for water level control in a conical tank process. Some authors further improved GA algorithms. For example, Chu, Yu, Dong, Lin, & Yuan (2020) applied a nondominated sorting genetic algorithm-II (NSGA-II), as a multiobjective optimization method derived from GA, to optimize a fuzzy proportional-integral-derivative (PID) controller for automatic train operation. El-Gendy, Saafan, Elksas, Saraya, & Areed (2020) proposed a hybrid of GA and PSO to tune the parameters of different adaptive PID controllers.

Mahmoodabadi & Nejadkourki (2020) applied FIS to regulate the control parameters of the PID controller for a quarter-car model, where the PSO algorithm is proposed to ascertain the optimum gains of the designed controller. The idea of PSO is inspired by the social behavior of bird flocking or fish schooling. The PSO metaheuristic is applied also by Zorić, Tomović, Obradović, Radulović, & Petrović (2019) for a self-tuning fuzzy logic controller of the piezo-fiber reinforced composite actuator.

Ajithapriyadarsini, Mary, & Iruthayarajan (2019) used differential evolution (DE) to optimize the gain of a fuzzy logic-DE algorithm-based PID controller. Ab Talib, Mat Darus, & Mohd Samin (2019) proposed an advanced firefly algorithm (AFA) for improving vehicle dynamics. Azizi, Ghasemi, Ejlali, & Talatahari (2019) used Multi-Verse Optimizer (MVO) for the optimization of a fuzzy controller applied to a seismically excited nonlinear building. Tremante, Yen, & Brea (2019) applied the Direct Search (DS) method, specifically the pattern search, for tuning of the membership functions of a FIS.

The Ant Colony Optimization (ACO) algorithm is applied by Aldair, Rashid, Rashid, & Alsaedee (2019) to tune and find the best parameters of the output membership function of the fuzzy controller for robot moves. Precup, Voisan, Petriu, Tomescu, David, Szedlak-Stinean, & Roman (2020) implemented a relatively new metaheuristic called Grey Wolf Optimizer (GWO) inspired by specific leadership styles of grey wolves.

Abd Ali, Hannan, Mohamed, Jern, & Abdolrasol (2020) presented a quantum-inspired lightning search algorithm (QLSA) to optimize the performance of the induction motor under different speed and load conditions. Karar, El-Garawany, & El-Brawany (2020) applied the Invasive Weed Optimization (IWO) algorithm inspired by the behavior of weed colonies.

Tab. 8 The recently used methods for FIS optimization (Source: Author)

Authors	Considered problem	Method of optimization	Type of FIS
Ab Talib, Mat Darus & Mohd Samin (2019)	Improving vehicle dynamics	AFA	Type-1
Ajithapriyadarsini, Mary & Iruthayarajan (2019)	PID controler in power system	DE	Type-1
Aldair, Rashid, Rashid, & Alsaedee (2019)	Robot moves modeling	ACO	Type-1
Azizi, Ghasemi, Ejlali & Talatahari (2019)	Behavior modeling of the building structure	MVO	Type-1
Tremante, Yen & Brea (2019)	Water tank system control	DS	Type-1
Yazid, Garratt & Santoso (2019)	Trajectory tracking of a quadcopter drone	ABC, GA, PSO	Type-1
Zorić, Tomović, Obradović, Radulović & Petrović (2019)	Controller of the piezo-fiber reinforced composite actuator	PSO	Type-1
Abd Ali, Hannan, Mohamed, Jern & Abdolrasol (2020)	Improving the performance of induction motor	QLSA	Type-1
Chouksey, Awasthi, & Singh (2020)	Solar power system modeling	IANN-PSO	Type-1
Chu, Yu, Dong, Lin & Yuan (2020)	Control of automatic train operation	NSGA-II	Type-1
El-Gendy, Saafan, Elksas, Saraya, & Areed (2020)	PID controller in the chemical process	GA-PSO	Type-1
Elias & Mat Yahya (2020)	Controller of a DC motor for the crane system	BSA	Type-1
Karar, El-Garawany & El-Brawany (2020)	Regulating anti-cancer drug delivery	IWO	Intuitionistic
Mohammadzadeh & Kayacan (2020)	Frequency regulation in ac microgrid	PSO-ABC	Type-2
Mahmoodabadi & Nejadkourki (2020)	PID controller for a quarter-car model	PSO	Type-1
Nagammai, Latha & Varatharajan (2020)	Water level control in a conical tank process	GA	Type-1
Nath, Mthethwa & Saha (2020)	Rainfall-Runoff modeling	ANFIS-PSO	Type-1
Precup, Voisan, Petriu, Tomescu, David, Szedlak-Stinean, & Roman (2020)	The trajectory of the robots	GWO	Type-1

Elias & Mat Yahya (2020) applied the bats sonar algorithm (BSA) which is inspired by the echolocation process of a colony of bats to find food or prey.

Mohammadzadeh & Kayacan (2020) proposed the particle swarm optimization and artificial bee colony algorithm (PSO-ABC). The algorithms based on the bees demonstrated very competitive results in optimization procedures. For example, Yazid, Garratt, & Santoso (2019) demonstrated that the ABC outperforms the GA and PSO approach in optimizing the fuzzy logic controller for trajectory tracking of a quadcopter drone. In this dissertation, a "shared partition" and "hybrid method" as segmented by Guillaume (2001) is combined. One class of shared partition is "One rule per pair" and the principle proposed by Wang and Mendel - WM (1992) is the most popular here.

When it comes to the use of metaheuristic algorithms based on artificial bees considering a longer period in the past, there are several cases in the literature where the authors performed the optimization of FIS by this approach (Table 10).

Some authors use the approach proposed by Karaboga (2005) named Artificial Bee Colony (ABC) optimization. The examples are the following. Chaiyatham, Ngamroo, Pothiya, and Vachirasricirikul (2009) optimized the load frequency control in the microgrid system. Habbi, Boudouaoui, Karaboga, and Ozturk (2015) proposed a methodology based on ABC to define Takagi–Sugeno (TS) fuzzy systems with enhanced performance from data. Konar, and Bagis (2016) applied different population-based approaches for the fuzzy modeling of the nonlinear systems and to perform the fuzzy rules optimization. They compared the performance of ABC, Particle Swarm Optimization (PSO) and Differential Evolution Algorithm (DEA).

On the other hand, some authors used the Bee Colony Optimization (BCO) approach for the optimization of FIS. BCO metaheuristic was proposed by Lučić, and Teodorović (2001, 2002, 2003a, 2003b). Caraveo, Valdez, and Castillo (2016) applied the BCO to optimize the FIS used as a water tank controller, which aims to control the water level in a tank, as well as to control the trajectory of the unicycle mobile robot. The same benchmark control problems were solved by Amador-Angulo, and Castillo (2018) who used BCO and type-2 fuzzy logic for tuning fuzzy controllers. Amador-Angulo, Mendoza, Castro, Rodríguez-Díaz, Melin, and Castillo (2016) proposed an improvement of BCO by dynamic adaptation of the algorithm's parameters. Olivas, Amador-Angulo, Perez, Caraveo, Valdez, and

Castillo (2017) made a comparison among Particle swarm optimization (PSO), BCO and the Bat Algorithm (BA), while Castillo, Valdez, Soria, Amador-Angulo, Ochoa, and Peraza (2019) compared the performance of BCO, Differential Evolution (DE), and Harmony Search (HS) algorithms in the optimization of fuzzy controllers.

Tab. 9 The use of the metaheuristic based on artificial bees for the optimization of FIS (Source: Author)

Source (Authors and year)	Type of artificial bees metaheuristic	The purpose of FIS optimization
Chaiyatham, Ngamroo, Pothiya, & Vachirasricirikul (2009)	ABC	Load frequency control in the wind-diesel system
Habbi, Boudouaoui, Karaboga, & Ozturk (2015)	ABC	To find a TS fuzzy model for a nonlinear plant model
Konar, & Bagis (2016)	ABC	Nonlinear system modelling
Caraveo, Valdez, & Castillo (2016)	BCO	Water tank controller; Control the trajectory of the unicycle mobile robot
Amador-Angulo, Mendoza, Castro, Rodríguez-Díaz, Melin, & Castillo (2016)	BCO	Controlling the trajectory of an autonomous mobile robot
Olivas, Amador-Angulo, Perez, Caraveo, Valdez, and Castillo (2017)	BCO	Controlling the autonomous mobile robot
Amador-Angulo, & Castillo (2018)	BCO	Water tank controller; Control the trajectory of the unicycle mobile robot
Castillo, Valdez, Soria, Amador-Angulo, Ochoa, & Peraza (2019)	BCO	Control of an Inverted Pendulum on a Cart; Water tank controller

2.5 A summary of the overview of current knowledge and a research plan

By analyzing the literature, it is concluded that the human factor is the far most common cause of RTAs. This was a motive to carry out research in this dissertation and to propose a decision-making tool that would be useful in the field of traffic safety, which is based on the examination of the psychological traits of drivers.

The technology development makes vehicles more affordable, which results in a rapid increase in vehicle ownership. On one hand, this results in an elevated likelihood of RTAs occurrence; however, on the other hand, this brings much more RTAs data, offering more possibilities to obtain the new knowledge in the traffic safety field. The wealth of RTAs data inevitably generates more explanatory variables that may provide more accurate models of explaining RTAs occurrence. However, it is known that "more is not always better", especially for the RTAs prediction. Considering a large number of variables may cause model overfitting (Sawalha and Sayed, 2006; Lin, Wang, and Sadek, 2015). Besides, this can impact the accompanying activities such as long execution time and unreliable prediction results (Lin, Wang, and Sadek, 2015; Fernández, Gómez, Lecumberry, Pardo, Ramírez, 2015). Having the previously stated in mind, one of the tasks in this dissertation was to narrow the choice of numerous instruments for the assessment of psychological traits that can explain driver behavior. The criteria about which of them to choose to be tested in the dissertation will be explained in the following few paragraphs.

In the literature, there are two psychological traits considered as the most dominant indicators of drivers who are identified by risky behavior on the road: aggressiveness and impulsiveness. This was a motive to choose two instruments that measure the mentioned two psychological traits.

However, since the aggressiveness and impulsiveness are still relatively similar psychological constructs (Critchfield, Levy, & Clarkin, 2004; Barratt, & Slaughter, 1998), in the instruments that measure them, some questions are often similar. This inspired the author of this dissertation to choose one of the instruments to be well established and frequently used in the literature and other that is relatively new and by that rarely implemented in the past. The psychological instrument more related to the aggressiveness and used a very limited number of times is the Aggressive Driving Behavior Questionnaire (ADBQ). On the other hand, the instrument for measuring impulsiveness that is widely implemented in the literature is the Barratt Impulsiveness Scale (BIS-11). BIS-11 is an instrument whose application is widespread both in clinical practice and in the professional literature dealing with the examination of various phenomena that can be related to impulsive behavior. This was precisely the motive to choose this well-established instrument which has been improved through practice and scientific research over time. Contrary, the ABDQ is a relatively new and insufficiently applied questionnaire. Although BIS-11 and ADBQ evaluate similar personality constructs, the advantage of ADBQ considering the topic of this dissertation is that its questions relate solely to the situations that the driver is facing in traffic.

Further, since the purpose of the model that should explain driver behavior is to offer as real as possible assessment of the examinee's propensity for RTAs, some additional questionnaires would be welcome. When searching the literature for some additional questionnaires to be a part of the model for explaining driver behavior, the intention was to adjust the model in the way to provide a space for corrective actions of the drivers who achieve low scores in the model and by that can be classified to a group of risky drivers. Here, it should be kept in mind that previously considered psychological traits - aggressiveness and impulsiveness, are mostly considered as innate traits, which means it is difficult to significantly change them in the education programs. The traits that can be considered as more acquired during life are related to attitudes and self-assessment (Iversen, & Rundmo 2004; Al-Rukaibi, Ali, & Aljassar, 2006; Sundström, 2008; Jain, Calvert, Clayton, & Parkhust, 2017). This was an inspiration to introduce two additional questionnaires measuring the mentioned traits in traffic to design the model for explaining driver behavior: the Manchester Driver Attitude Questionnaire (DAQ), and the Questionnaire for Self-Assessment of Driving Ability. These two questionnaires were used in several studies that addressed driver behavior. However, they demonstrated very good results in explaining the authentic behavior of drivers (Gordon, 2007; Tronsmoen, 2011). Thus, it is interesting and important to examine whether driver propensity for RTAs is more influenced by innate personality dispositions or acquired behaviors such as attitudes and self-perception of driving ability. This is especially useful for the recommendations related to the design of driver training programs for obtaining a driving license, as well as for the creation of programs and campaigns for traffic safety improvements.

In the dissertation, after the implementation of the considered instruments, certain data would be collected. Each participant would achieve certain scores on the implemented psychological instruments, which describes the personality traits related to driver behavior of this individual. These scores can be seen as input variables. Additionally, each participant would report the number of accidents in his driving history, which can be considered as an output variable. Here, it should be noticed that the proposed models tend to exclude the impact of age and driving experience on the number of experienced RTAs and to focus exactly on the relationship between the driver's characteristics and RTAs. This is further explained in the methodological part of the dissertation. Therefore, the tasks would be to examine a relationship between the considered input and output variables (Table 10). By reviewing the literature, it is concluded that this relationship can be determined by two general approaches: statistics and fuzzy logic. Speaking about the statistical methods, a convenient statistical method is the hierarchical regression analysis when the output variable is presented as the number of experienced accidents. If the output variable is presented in a binary way (driver participated in accidents or no), then a convenient statistical method is the binary logistic regression.

Tab. 10 The structure of collected data (Source: Author)

Input data	Output data
Score from the ADBQ	The number of road traffic accidents
Score from the BISS - 11	
Score from the Manchester DAQ	
Score from the Questionnaire for Self-assessment of Driving Ability	

In this dissertation, the hierarchical linear regression will be used to assess a relationship between the variables of interests, in this case, the scores from four considered psychological instruments and the number of experienced RTAs. Further, it can be very useful to compare the obtained results with another statistical method - binary logistic regression. However, in this case, the dependent variable should be arranged in a binary manner, which means that the participant should be grouped into two groups: those who participated in RTAs and those who did not.

Further, the implementation of fuzzy inference systems in the field of explaining driver behavior is very meaningful. For this aim, four achieved scores from psychological instruments will be used as the input variables of the proposed FIS, and the number of RTAs as an output. A result of the FIS represents the quantification of driver propensity for RTAs.

Therefore, various FIS structures will be designed and tested in this dissertation. The Wang and Mendel (WM) approach for generating fuzzy rules will be applied combined with a metaheuristic algorithm based on Bee Colony Optimization (BCO) to perform the optimization of different FISs.

By analyzing Table 9, where the papers that use the metaheuristic based on artificial bees are listed, it can be concluded that there is no example of using this type of algorithm for explaining driver behavior. This is precisely one of the motives to carry out the research as proposed in this dissertation. The overall conclusion of the literature review would be that the proposed methods would support in the best way the investigation about a relationship between the psychological traits and driver behavior. Besides, the implementation of the proposed methods would lead to the design of a decision-making tool that can be used for various purposes in the field of traffic safety. Based on the literature review, a research plan is structured as shown in Figure 1.

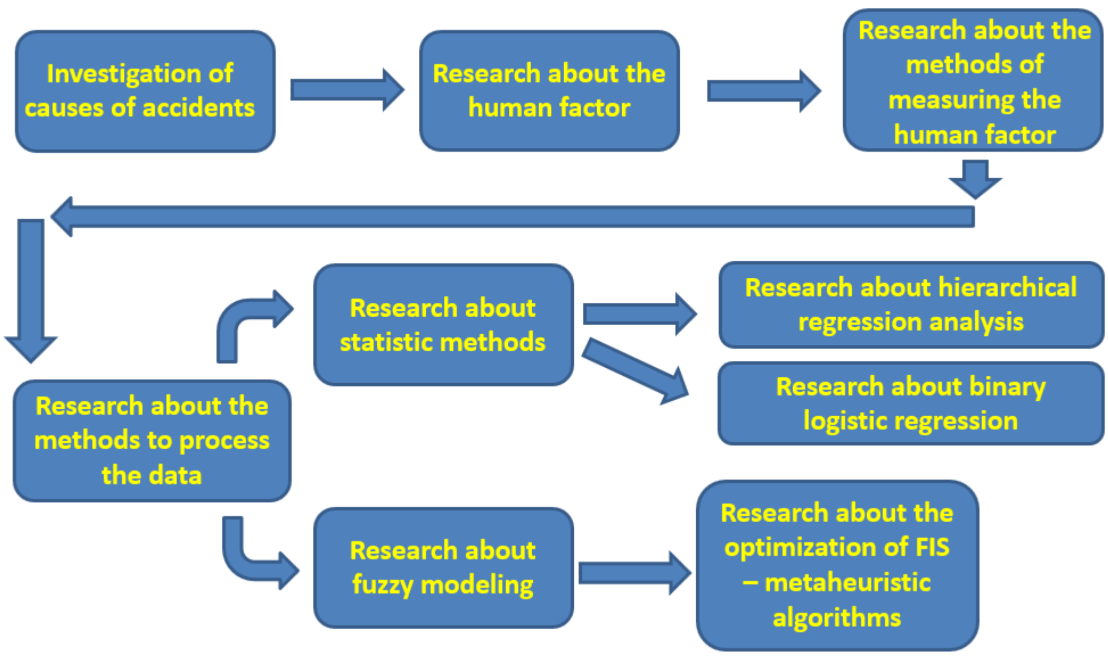


Fig. 1 The structure of the literature review and research plan (Source: Author)

3 The main objective of the dissertation

One of the crucial questions in the transportation field is how to reduce the number of lost lives on the roads. A human is the most important and also the most complex factor in traffic safety. When participating in traffic, the driver is expected to possess adequate abilities, knowledge, and skills and to perform safe driving maneuvers. The lack of any of these elements can lead to making mistakes which can result in an RTA. When it comes to the analysis of the dominant personality traits of the drivers, many studies have shown a strong connection between risk perception and involvement in accidents. By understanding the factors affecting the RTAs occurrence, the ability to define adequate measures increases which should reduce the negative consequences of inappropriate behavior.

The primary objective of the research is to propose the most appropriate methodology for modeling driver behavior based on a detailed investigation of the literature and current methods of explaining driver behavior. To achieve a conclusion about the most convenient methodology, different methods are compared. The final result of modeling would be a decision-making tool for explaining driver behavior, to be used in various situations in transportation, with the main aim to improve traffic safety and save the lives of people.

To achieve the explained primary objective, it is necessary to fulfill the following partial objectives:

- To carry out a survey that implements relevant psychological instruments, as well as the demographic questionnaire;
- To perform the statistical analyses of collected data;
- To implement the hierarchical regression analysis to examine a relationship between the variables of interest;
- To implement the binary logistic regression to examine a relationship between the variables of interest;
- To implement a fuzzy logic for modeling driver behavior;
- To propose an algorithm based on BCO metaheuristic for the optimization of FIS for modeling driver behavior.

4 Overview of the research methods used to fulfill the objective of the dissertation

In this dissertation, the general, as well as specific scientific methods are used. General scientific methods are the following: analysis, synthesis, deductive and inductive reasoning, abstraction and concretization, analogy and comparison, as well as modeling. On the other hand, the applied specific methods are the following: for data collection – five types of questionnaires (a demographic one and four psychological instruments), hierarchical regression analysis, binary logistic regression, fuzzy logic, and BCO metaheuristic.

4.1 General scientific methods

General scientific methods, or also known as basic methods, can be classified into two categories: analytical methods (analysis, deductive reasoning, abstraction) and synthetic methods (synthesis, inductive reasoning, concretization). Besides these mentioned methods, in the dissertation, there are also used analogy and comparison, modeling, and method of searching literature sources.

4.1.1 Analysis and synthesis

The analysis as a research method can be seen as a decomposition of the subject of research into its constituent parts and searching for the rules that exist between these parts or inside them. The subject of research can always be considered as a certain system, which has its structure, elements, connections, and relations between them. The complexity of a system of analysis allows the object to be explored as a whole or to explore only one of its properties, one part, one or a set of relations, at one time (a certain period) or in several periods.

Contrary to the analysis, the synthesis represents a merging of more elements into one whole. As the general method of scientific knowledge, synthesis is the understanding of the knowledge of complex systems through their individual and special parts, by their merging, and by placing them in various possible relationships and connections.

4.1.2 Deductive and inductive reasoning

From the scientific field that considers the thinking, analysis, and understanding of the issues of logic, it follows that deduction is understood as a form of inference, primarily syllogistic. By deduction, new conclusions are drawn analytically, mentally - logically from the premises - of the already formed conclusions or statements according to the established procedure. Only the conclusions drawn in this way are absolutely true because they are analytical (Miljevic, 2007). In that sense, unlike induction, as a synthetic and generalizing methodological procedure of acquiring general knowledge from and on the basis of special and individual knowledge, a deduction is an analytical methodological procedure, which acquires special knowledge from and on the basis of general knowledge.

4.1.3 Abstraction and concretization

In its essence, the subjects of abstraction are concepts, attitudes, judgments, conclusions, and other more complex and broader systems of expression of opinion in which, as a rule, thinking abstraction is applied. The basic scientific method of abstraction has an established methodological procedure of abstraction. In the process of scientific work, the procedure of abstraction is a procedure of deliberation, which is focused on the subject (general and special) and which takes place according to certain rules. This procedure follows the analysis as a research method and reveals the obtained parts in the analysis of the object, its properties, contents, forms, moments, relations, etc.

The subject of concretization, in general, is the relationship between the general, the special, and the individual, starting from the more general. At the same time, By concretization, the relations between the abstract and the concrete are learned. The scientific procedure of concretization consists in ascertaining an abstract concept, and then adding one or more labels, bringing that abstract issues closer to the concrete (Miljevic, 2007).

4.1.4 Analogy and comparison

The analogy is a reasoning process of transferring characteristics or meaning from a particular subject, which can be considered as the analog or source, to another, which can be seen as the target. Therefore, the analogy is a process of generating conclusions from one particular to another particular, as opposed to deduction, or induction, where at least one of the premises, or the conclusions, is general rather than particular.

A similar concept is a comparison as a research method, where the essence is in evaluating two or more phenomena by discovering the relevant, comparable issues of each phenomenon, and then determining which attributes are similar to the other, which are different, and to what degree. The differences may then be evaluated to determine which phenomenon is best designed to achieve a particular aim.

4.1.5 Method of modeling

Modeling is a rational, systematic, complex procedure of adequate presentation of essential characteristics of a process, phenomenon, or reality or their ideas as a complete system. In other words, modeling is the process of making a model. A model is an imitation, prototype, or projection of an object of a part of the existing, past, and possible future reality. A result of the modeling can be a material thing; however, even most common is to model the relationships among certain phenomena and to form a mathematical structure that would imitate the real behavior of the considered system.

4.1.6 Method of searching the literature sources

As one of the first steps in preparing the research for the purpose of this dissertation was searching for adequate literature sources related to the topic. The two literature databases are used: *Web of Science* and *Google Scholar*. The main keywords in the searching procedure were: traffic safety, road traffic accidents, driver behavior, psychological traits, psychological instruments, data processing, hierarchical regression analysis, binary logistic regression, fuzzy logic, optimization of fuzzy inference system, bee colony optimization.

4.2 Specific scientific methods

When it comes to specific scientific methods, the methodology of research covers several areas. Since the primary objective is to propose a methodology for modeling driver behavior, firstly, the psychological instruments to assess the drivers' personality traits should be considered. These instruments had been chosen in the way to describe as accurately as possible the driver propensity for RTAs. Further, a survey should be carried out to collect data about drivers. The third methodological issue relates to the implementation of statistical techniques: the hierarchical regression analysis and binary logistic regression. Further, the design of a FIS for modeling driver behavior should be done. This would be a starting point for the optimization procedure. Finally, the optimization of FIS will be performed by the BCO metaheuristic. As a result of the optimization procedure, there is a FIS representing a model for explaining driver behavior with the minimal deviations from empirical data.

4.2.1 Data collection method – questionnaires

The first implemented questionnaire relates to general data about the participant, where the most important question considering the topic of this dissertation is about the number of RTAs experienced by a driver. In addition to the demographic questionnaire, four questionnaires for assessing personality traits were applied: Barratt Impulsiveness Scale – BIS-11, Aggressive Driving Behaviour Questionnaire – ADBQ, Manchester Driver Attitude Questionnaire - DAQ, and Questionnaire for Self-Assessment of Driving Ability.

Demographic and driving history questionnaire

The demographic and driving history questionnaire consists of the most relevant questions on the demographic characteristics of respondents and issues related to road traffic safety. The complete questionnaire is offered in Appendix A1. Some of the questions relate to gender, age, driving experience, annual mileage, the number of experienced RTAs, category of vehicles that the respondent operates, etc. A multiple-choice question type was used with sufficiently detailed categories offered.

Aggressive Driving Behaviour Questionnaire

ADBQ was designed by Mouloua et al. (2006). The intention of researchers in the design of this questionnaire was to create an instrument with good predictive power considering aggressive situations that are typical in driving. The mentioned situation can be the gestures directed toward other drivers, or other aggressive outbursts, such as passing through a red light at an intersection. The instrument contains 20 questions. The respondents were asked to assess the likelihood of manifestation of aggressive driving using the 6-point scale. Results are given in the range of 1 = Never to 6 = Almost always. The questionnaire can be found in Appendix A2.

Barratt Impulsiveness Scale

BIS-11 is an instrument for the assessment of impulsivity as a personality trait. In this research, a version of BIS-11 constructed by Patton et al. (1995) is used. The questionnaire consists of 30 questions that cover a variety of situations that characterize the impulsive behavior and habits of impulsive behavior. The questionnaire is given in Appendix A3. It was expected from the respondents, by using the 4-point Likert scale, to estimate how often they agree with the statements which describe the most representative impulsive habits and practices. The scaled responses correspond to the following statements: from 1 = Never / rarely to 4 = Always / almost always. For certain questions in the questionnaire, the inversion of the response values was made.

Manchester Driver Attitude Questionnaire

DAQ is a questionnaire for the assessment of attitudes toward risk propensity while driving constructed by Parker, et al. (1998). The questionnaire consists of 20 questions with a scale answers from 1 = Strongly Disagree to 5 = Strongly Agree. Most questions refer to the typical traffic situations that can be characterized as high-risk ones. DAQ includes statements relating to speeding, drink-driving, close-following, and dangerous overtaking. Here the scores are arranged in the way that higher scores correspond to higher risk propensity while driving. Scores of subjects can range from 20 to 100 points. The questionnaire can be found in Appendix A4.

Questionnaire for Self-Assessment of Driving Ability

The questionnaire for self-assessment of driving ability was proposed by Tronsmoen (2008). It is an inventory of statements about how the drivers react in certain traffic situations. Based on the responses, it is possible to obtain information about what picture the respondents create about themselves as drivers. There are 22 questions and answers in the form of a 4-point Likert scale. Answers ranged from 1 = Strongly Disagree to 4 = Strongly Agree. A higher score on the test corresponds to a better evaluation of own driving abilities. The questionnaire is given in Appendix A5.

Process of data collection

A convenience sampling technique (a non-probability technique), was implemented. This technique implies a sample that is an available source of data for researchers. In this survey, two types of examination strategy were implemented, one for the drivers of privately owned vehicles, and another for professional drivers. The participating professional drivers completed paper-based questionnaires, while drivers of privately owned vehicles completed web-based questionnaires. The drivers of privately owned vehicles in the sample are mainly people with whom some sort of the previous contact existed in the past or they are friends of these people. The link for web-based questionnaires was shared to participants by e-mail. The online response rate was 65.6 %, which is well above the average of 34.2 % determined by Poynton, DeFouw, and Morizio (2019).

To collect data on professional drivers, 12 transport companies (with some sort of previous cooperation with the author) were contacted. This might explain why there was a very high response rate, because of this connection. Namely, all the contacted drivers filled in the questionnaires.

In the calculation process, the results from four considered questionnaires and the number of RTAs are marked in the following way:

- x_1 – score from ADBQ,
- x_2 – score from BIS-11,
- x_3 – score from DAQ,
- x_4 – score from the Questionnaire for Self-Assessment of Driving Ability and
- y – the number of RTAs.

4.2.2 Hierarchical regression analysis

To analyze the relationship between experiencing traffic accidents and the observed characteristics of the driver, the hierarchical regression analysis will be performed.

In general, the hierarchical regression analysis is to be used if there is a need to examine whether the independent variables explain a statistically significant amount of variance in the dependent variable after accounting for all other considered variables. The procedure implies forming several regression models by adding variables to the previous model at each step. These models are often called “blocks” or “steps” in the hierarchical regression analysis. In this way, the blocks are compared and a conclusion should be reached about the impact of each independent on the dependent variable, i.e. it should be determined whether newly added variables show a significant improvement in R^2, which is the proportion of explained variance in dependent variable by the model (UVL, 2019).

For example, let us assume that relationships between the psychological traits of driver and RTAs should be examined and that the aggressiveness is known as a good predictor variable. In the next block, the independent variable impulsiveness will be added to investigate its impact on RTAs.

The first block typically includes demographic information such as age and gender, together with the intercept, which is a constant for adjusting the equation on the right side to the actual values on the left side. The first block is introduced to get the information about the amount of explained variance in dependent variable by these first two controlling variables. They are named "controlling" because their effect is controlled, i.e. "removed" in the next blocks. Further, in the next step, in Block 2, a known important variable can be added. The difference in this block, compared to the previous, is that the possible effect of Age and Gender can be removed here, and it can be examined whether this block of independent variables is still able to explain some of the remaining variance in the dependent variable. Then, to form Block 3, the variable that should be examined is added, in this example - impulsiveness.

Block 1: Impact on RTAs = Intercept + Age + Gender (R^2 = .023)

Block 2: Impact on RTAs = Intercept + Age + Gender + Aggressiveness (R^2 = .119)

Block 3: Impact on RTAs = Intercept + Age + Gender + Aggressiveness + Impulsiveness (R^2 = .186, ΔR^2 = .067)

To conclude whether the impulsiveness explains better the propensity for RTAs together with aggressiveness, Blocks 2 and 3 should be compared.

If the difference of R^2 between Block 2 and 3 is statistically significant, the impulsiveness added in Block 3 explains the RTAs above the variables in Block 2. In this example, it should be examined if the increased R^2 .067 (.186 – .119 = .067) is statistically significant. If this assumption is confirmed, the impulsiveness explains an additional 6% of the variance in the occurrence of RTAs and it is statistically significant.

To perform the calculations related to the hierarchical regression analysis, in this dissertation a specialized statistical software will be used – *IBM SPSS Statistics*.

4.2.3 Binary logistic regression

The binary logistic regression is the statistical technique used to predict the relationship between predictors or independent variables and a predicted variable or the dependent variable, where the dependent variable is binary, e.g. participation in RTAs (yes vs. no). The logistic function is a model of the well-known sigmoid function, which is shown in Figure 2.

As explained, the observations can be of class 0 or 1. To compute the probability (p) that an observation belongs to class 1 (y = 1), Eq. (1) should be applied. The probability p of the value labeled "1" can vary between 0, which implies a certainty that the value is "0", and 1, which depicts a certainty that the value is "1".

$$p = P(y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k)}} \tag{1}$$

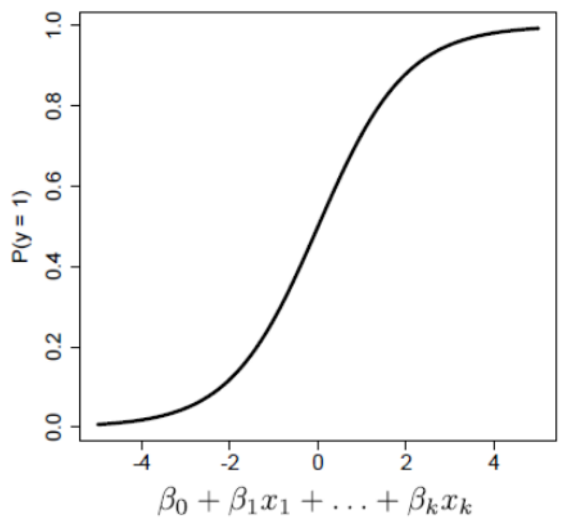


Fig. 2 Mathematical interpretation of sigmoid function (Source: Garcia, 2018)

In the logistic regression, the log-odds (the logarithm of the odds) for the value labeled "1" is a linear combination of one or more independent variables, i.e predictors. This linear relationship can be expressed by Eq. (2), where *l* is the log-odds, *b* is the base of the logarithm, and β_i are parameters of the model.

$$l = \log_b \frac{p}{1 - p} = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k \tag{2}$$

The function that converts log-odds to probability is the logistic function, as an example of a sigmoid curve, which is also the reason why this technique is called the logistic regression analysis. The unit of measurement for the log-odds scale is called a logit, from the words "logistic unit".

The coefficients β ($\beta = 1, k$) values, are selected to maximize the likelihood of predicting a high probability for observations belonging to class 1, and predicting a low probability for observations belonging to class 0 (Garcia, 2018). Therefore, the main task in the logistic regression is to find the most suitable β coefficients.

The chi-square is used to statistically test whether including a variable reduces badness-of-fit measure. If chi-square is significant, the variable is considered to be a significant predictor in the equation.

To perform the calculations related to the binary logistic regression, in this dissertation a specialized statistical software will be used – *IBM SPSS Statistics*.

4.2.4 Multiple regression analysis

Multiple regression analysis is a statistical method used for predicting the unknown value of a variable, often named dependent variable, from the known value of two or more variables - also called the predictors or independent variables. The multiple regression analysis equation is defined as follows:

$$y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n \tag{3}$$

The Eq. (3) means that it is possible to predict the value of y based on given values of x_1, x_2, .. , x_n. Therefore, the task of multiple regression analysis is to determine the most appropriate values of *b* coefficients b_0, b_1, … , b_n.

In this dissertation, for the calculation purposes related to the multiple regression analysis, a specialized *IBM SPSS Statistics* software will be applied.

4.2.5 Implementation of fuzzy logic

The fuzzy logic was proposed by Zadeh (1965) offering the following basic definition: A fuzzy set *A* in *X* is characterized by a Membership Function (MF) $\mu(x)$, which assigns each point in *X* a real number in the interval [0, 1], with the value of $\mu(x)$ where *x* represents the "grade of membership" of *x* in *A*.

In the modeling process, the input variables will be the scores (results) from four implemented psychological instruments, and output will be the number of RTAs. Based on this, various FIS structures will be tested which would make the minimum error in the description of the data. Four types of FIS will be considered, as follows: one input–one output system, two input–one output system, three input–one output system, and four input–one output system. The results of the test should lead to a conclusion as to which psychological instrument, or which combination of two, three, or all four of them, provides the best prediction results regarding driver propensity for RTAs.

To describe variables by MFs in the FIS, the following approach is implemented. Let us assume that each input variable *j* is defined by N_j MFs where N_j is an odd number starting from 3, because there are at least three MFs that explain one variable. The entire interval of possible solutions for variable j is from I^j_{min} to I^j_{max}. The mean ($\overline{X}_j$) and extreme values from the empirical sample are taken into account when defining the points with maximum degrees for the MFs *number 1*, $\left\lceil \frac{N_j}{2} \right\rceil$ and N_j. Therefore, in this method, the positions of points with the maximum degree for all MFs can be determined by Eq. (4), where X^j_{min} is the minimum value from the sample for variable *j*, and X^j_{max} is the maximum value from the sample for variable *j*. $P^j MF_i$ is the position of a point with the maximum degree for MF *number i*, for variable *j*.

$$P^j MF_i = \begin{cases} [I^j_{min}, X^j_{min}], & i = 1\,,\ I^j_{min} < X^j_{min} \\ X^j_{min} + \dfrac{\overline{X}_j - X^j_{min}}{\left\lceil \frac{N_j}{2} \right\rceil - 1}(i-1), & \forall\, i = 1, 2, .., \left\lceil \frac{N_j}{2} \right\rceil \\ \overline{X}_j + \dfrac{X^j_{max} - \overline{X}_j}{\left\lceil \frac{N_j}{2} \right\rceil - 1}\left(i - \left\lceil \frac{N_j}{2} \right\rceil\right), & \forall\, i = \left(\left\lceil \frac{N_j}{2} \right\rceil + 1\right), .., N_j \\ [X^j_{max}, I^j_{max}]\,, & i = N_j\,,\ X^j_{max} < I^j_{max} \end{cases} \tag{4}$$

The basis for fuzzy rules is essential for the performance of FIS. In this dissertation, a well-known approach for defining fuzzy rules proposed by Wang and Mendel (1992) is used. This method is widely used in the literature. Some examples could be found in the papers of Chang, Hieh, and Liao (2005), to solve a problem of due-date assignment in semiconductor manufacturing factory; D'Andrea and Lazzerini (2013) assessed the condition of solar photovoltaic energy installation and Jovcic, Prusa, Dobrodolac, and Svadlenka (2019) proposed a decision-making tool in third-party logistics (3PL) provider selection.

The Wang-Mendel method consists of five steps. Step 1 divides the input and output spaces of the given numerical data into fuzzy regions. For each variable used in the research, the domain interval was determined, that is, the interval of the possible values of variables. Each domain interval was divided into 2N+1 regions. The length of these regions and fuzzy MFs that describe them were determined based on the logic explained in Eq. (4).

Step 2 generates fuzzy rules from the collected data. In the beginning, one data pair is used for the construction of one fuzzy rule. Then, this data pair should be assigned to the regions with a maximum degree. Thus, finally, one fuzzy rule from one pair of desired input-output data is obtained. The IF part is composed of the names of regions with the maximum degree for input variables, and the THEN part from the name of the region with maximum degree for output variables.

In Step 3, a problem of conflicting rules needs to be solved. These are the rules that have the same IF part, but a different THEN part. For this purpose, each of the formed rules should be assigned a degree, defined by Eq. (5) for the case when a rule is defined as follows: "IF x_1 is A and x_2 is B, THEN y is C".

$$D(Rule) = \mu_A(x_1) * \mu_B(x_2) * \mu_C(y) \tag{5}$$

D(Rule) is a degree of a rule, $\mu_A(x_1)$ is a value of the membership function of the region A when the input value is x_1, etc. In a conflict group, only the rule that has a maximum degree should be accepted.

Step 4 makes a combined fuzzy rule base, which consists of rules obtained from empirical data and linguistic rules acquired from a human expert. Finally, Step 5 determines a mapping from input to output space using a defuzzification procedure.

Finally, when all parameters of FIS are defined, its performance should be tested. In this process, the objective function expressed by Eq. (6) is used.

$$\text{Minimize} \quad CD = \sum_{z=1}^{PA} |y^z - FIS(z)| \tag{6}$$

where *CD* is the cumulative deviation between the empirical data and results of created FIS structures, *PA* is the number of participants in the sample, y^z is the number of RTAs that participant *z* experienced in the driving history and *FIS(z)* is the result of FIS for the participant *z*. Therefore, the *CD* is a measure that describes how well a FIS describes the empirical data.

4.2.6 Implementation of BCO metaheuristic

The general principles of BCO metaheuristic and its comprehensive description can be found in Teodorović (2009). The main characteristic of BCO is that the artificial bees collectively search for the best solution and each bee is independent in the searching procedure. However, in certain moments, they compare their obtained solutions and a bee decides to continue its search following some other bee or be loyal to its own solution. The main idea behind is that certain bees should follow the bees with better solutions in order to find as good as possible solution. When a bee searches for a solution, this part of the algorithm is called *forward pass*, while the procedure of returning to the hive and comparison of achieved solutions is called a *backward pass*. All decisions are made with an adequate probability level, having in mind the quality of current achieved solutions. Instead of deciding based on the absolute values of achieved solution, the probability in the bee's decision-making to follow other bee or to stay loyal to its solution is introduced in order to avoid being trapped in local optimums.

The main attributes of the BCO algorithm are the following (Nikolić, & Teodorović, 2013):

B – the number of bees involved in the search procedure,

IT – the number of iterations,

NP – the number of forward and backward passes in one iteration,

NC – the number of solution changes in one forward pass,

S – the best-known solution.

When it comes to the implementation of BCO algorithm for the purpose of FIS optimization, the following concept is introduced. Let us assume that the vertices of a triangular MF are marked with A, B, C, where their positions are defined by values of *x* and *μ(x)*. The vertices A, B, C are distributed along x_i axis by ascending order, which means that the value *x* for the vertex A is the smallest, for B - middle and for C - the highest. In the BCO algorithm, each vertex of MF is considered as a parameter $P_f(ch)$ ($f = 1, NP; ch = 1, NC$) to be changed NC times in one forward pass. In the proposed BCO algorithm, for each approach for the design of MFs and for each considered variable, for the MF *number 1* just the parameter of MF that is characterized by the highest value of *x* is changed. Conversely, for the MF *number* N_j the changes are made just for the parameter of MF that is characterized by the smallest value of *x*. For all other MFs of a variable, all three parameters of an MF are changed. Therefore, if a variable is described by five MFs, this variable would be described by 11 parameters. After each change of a parameter, the fuzzy rules should be set to form a complete FIS. This is done using the method proposed by Wang and Mendel (1992). When a FIS is completely designed, the effects of each change should be tested on the empirical data by applying Eq. (6).

The concept of the BCO algorithm is graphically shown in Figure 3. In this case, it is assumed that *NC*=2 which means that in a forward pass there will be two changes of the parameter. In the proposed BCO algorithm, each parameter $P_f(ch)$ is changed by the new value $P_f'(ch)$ according to Eq. (7) and after each change and generation of new fuzzy rules, the performance of newly created FIS is evaluated by Eq (6).

$$P_f'(ch) = P_{fmin} + \left(P_{fmax} - P_{fmin}\right) * rand_{f,ch} \tag{7}$$

P_{fmin} is the minimal value of the parameter P_f, P_{fmax} is the maximum value of the parameter P_f ($f = 1, NP$), and $rand_{f,ch}$ is a random number in the interval from 0 to 1 which changes its value *NP* x *NC* times in each iteration ($ch = 1, NC$).

In Figure 3, the first row represents a set of possible values that the first parameter can take. Although this is an extremely large range of possible values, it is a finite number denoted by letter *n*. In Figure 3, *n* has a different notation in each forward pass in order to demonstrate that different parameters can take other *n* possible values at different variable domains across x_i axis. Therefore, a set of possible values that considered parameters can take is referenced as n_{Pf}, where *P* in the index indicates that it is a possible value of a parameter and *f* gives the information about which of *NP* parameters is changing (f = 1, *NP*).

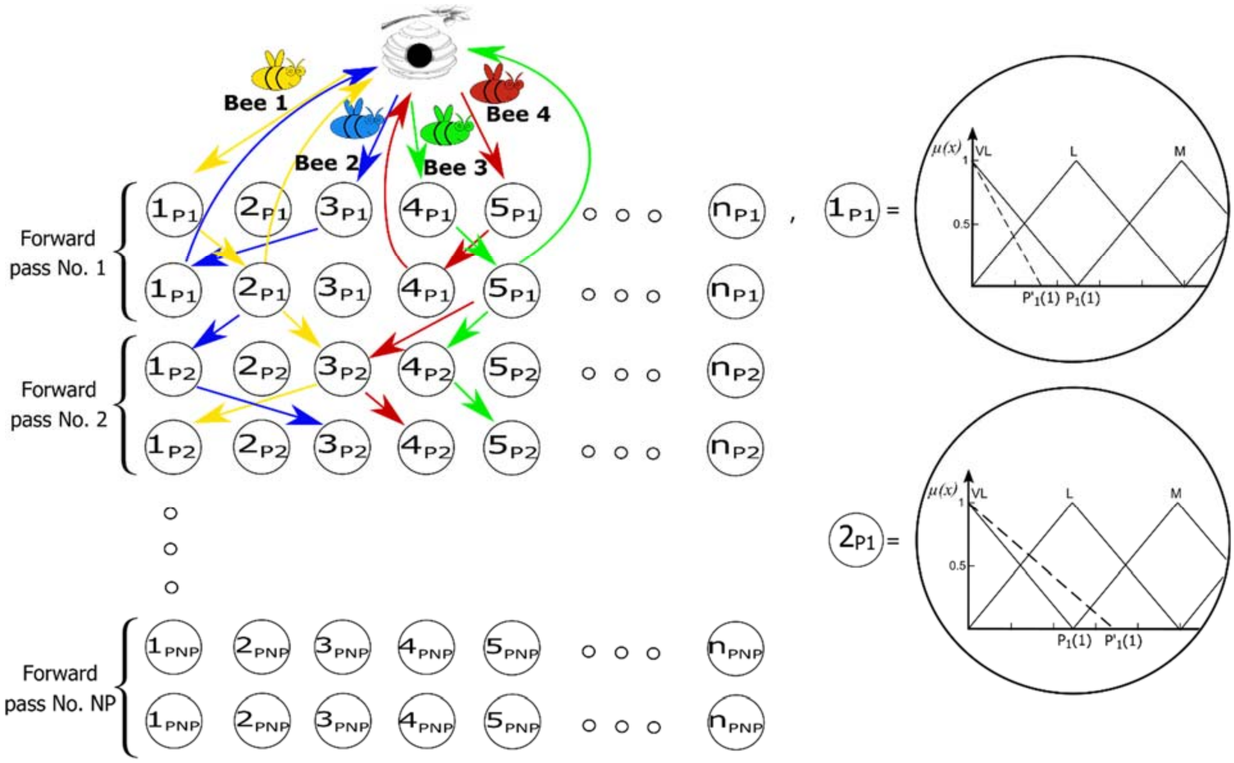


Fig. 3 The concept of BCO algorithm for the case *B*=4, *NC*=2 (Source: Author)

In the first forward pass denoted by No. 1, each bee takes one of n_{P1} values for the first parameter $P_1(1)$. Based on the selected value, a bee generates the new FIS and the value of its objective function is calculated. Then each bee takes some other of n_{P1} values for the same first parameter $P_1(2)$ and the new values of objective functions are calculated. Since the *NC* = 2, after two changes a bee should decide which of two values will take and bring to the hive for comparison with other bees. A decision about which change a bee should take is made by a certain probability level. For this purpose, it is introduced a probability of choosing one of two values in this case (PR_f) which is calculated based on a well-known *Logit* model. Having in mind that the objective function relates to minimization, the calculation of PR_f is done as shown in Eq. (8) (Marković, 2007).

$$PR_f = \frac{e^{(1-CD_f)}}{\sum_{f=1}^{NC} e^{(1-CD_f)}} \tag{8}$$

CD_f is the value of the objective function for change number *f*. To make a selection decision, a number from the interval (0,1) is randomly generated. Based on the calculated probability value PR_f and the value of a randomly generated number, a bee decides which value of the parameter will adopt in the considered forward pass.

A concept of bees' solutions comparison is also based on the probability. First, a bee should decide to be loyal or not to its obtained solution. This procedure can be done as explained by Nikolić (2015). The quality of the solutions generated by bees is normalized as shown in Eq (9):

$$N_b = \frac{CD_{bmax} - CD_b}{CD_{bmax} - CD_{bmin}} \tag{9}$$

where N_b is a normalized value of objective function obtained by *b-th* bee, CD_{bmax} is the highest value of objective function found by all bees, CD_b is the value of objective function found by *b-th* bee and CD_{bmin} is the lowest value of objective function found by all bees.

A bee decides whether to remain loyal to its solution at the basis of probability (PRL_b) calculated as presented in Eq. (10):

$$PRL_b = \mathrm{e}^{-(N_{bmax} - N_b)} \tag{10}$$

where N_{bmax} is the maximum normalized value of objective function considering all bees.

If the bee decides not to be loyal to its solution, it chooses which bee to follow. A probability that the bee that is not loyal will follow the *b-th* bee (PRF_b) is expressed by Eq. (11) where L is a set of loyal bees.

$$PRF_b = \frac{N_b}{\sum_{l \epsilon L} N_l} \tag{11}$$

In the illustrated case in Figure 3, the Bees 1 and 3 remained loyal to their previous solutions, while the Bees 2 and 4 abandoned their solutions and decided to continue their search following the solutions of the Bee 1 and 3, respectively.

The basic steps of BCO algorithm implemented for the purpose of FIS optimization are presented in Table 11. In the proposed pseudocode, the used symbols are as previously defined (inputs: *B*, *IT*, *NP*, *NC*; output: *S*). A case when the proposed algorithm is performed ones, including IT iterations, will be called an experiment (E). It is welcome to repeat the experiment more times and to compare the results.

Tab. 11 Pseudocode of implemented BCO algorithm for FIS optimization (Source: Author)

1. for e = 1 to E
2. for t = 1 to IT
3. for b = 1 to B
4. Assign an initial solution to the bee b.
5. for f = 1 to NP
6. for b = 1 to B
7. for ch = 1 to NC
8. Evaluate the performed changes in the solution of the bee b. Chose one change considering the obtained values of objective function.
9. for b = 1 to B
10. Based on values of objective function for each bee, make decision whether the bee b is loyal to its own solution. If the bee b is not loyal, chose the bee to be followed by the bee b.
11. Evaluate all solutions and find the best one S.
12. Output the best solution for each iteration.
13. Output the best solution for each experiment.

4.3 The implemented software

IBM SPSS Statistics is a powerful statistical software platform. In this dissertation, it is used for calculations related to hierarchical regression analysis and binary logistic regression.

MATLAB is a programming platform designed specifically for engineers and scientists. It runs by a specific MATLAB language, a matrix-based language allowing the most natural expression of computational mathematics. In this dissertation, the version MATLAB R2020a is used for design and testing FIS structures and in the process of their optimization by BCO metaheuristic. Even though MATLAB includes a fuzzy logic toolbox offering the graphical interface, all the procedures are realized in the programming workspace because the optimization procedure of FIS implies an extensive programming code.

Inkscape is an open-source vector graphics editor. It offers a rich set of features and is widely used for both artistic and technical illustrations.

Microsoft Office package is used for data manipulation (*Excel*), text processing (*Word*), and presentation activities (*PowerPoint*).

5 Results and discussion

The main goal of the dissertation is to propose the most appropriate methodology for modeling driver behavior and accordingly to design a convenient decision-making tool for explaining driver behavior. A direction for the creation of the most appropriate methodology is obtained by a detailed review of the literature, which is presented in the second chapter of this dissertation; as well as by empirical research, which results are presented exactly in this chapter. To collect the primary data, it is concluded that the most appropriate solution is a combination of several questionnaires: the demographic and driving history questionnaire, Aggressive Driving Behavior Questionnaire – ADBQ (marked with x_1 in the calculations), Barratt Impulsiveness Scale – BIS-11 (marked with x_2), Manchester Driver Attitude Questionnaire – DAQ (marked with x_3), and Questionnaire for Self-Assessment of Driving Ability (marked with x_4). As previously explained, the number of RTAs is marked with y. For processing the data, there are two general approaches: statistical and fuzzy approach, and the presentation of the results will be arranged accordingly.

The results of the research and implemented methods are structured in five subsections. The first is devoted to the results of the applied questionnaires. The second subsection shows the results of hierarchical regression analysis, followed by the third where the results of binary logistic regression are. The fourth part is related to the implementation of FIS for driver behavior modeling, while in the fifth there are the results of the proposed BCO algorithm for FIS optimization.

5.1 The results of the demographic and driving history questionnaire

Characteristics of a sample

The sample included 305 drivers, comprising 103 drivers of privately owned vehicles, 100 bus drivers, and 102 truck drivers. The sample comprised 88 % male and 12 % female drivers (Figure 4). This relationship was expected due to the demanding nature of professional driving and the fact that generally, a large majority of drivers are male. Concerning age structure, 18 % of the sample were aged 18 to 30 years old, 56 % between 31 and 45, 17 % between 46 and 60, and 9 % above 60 years old (Figure 5).

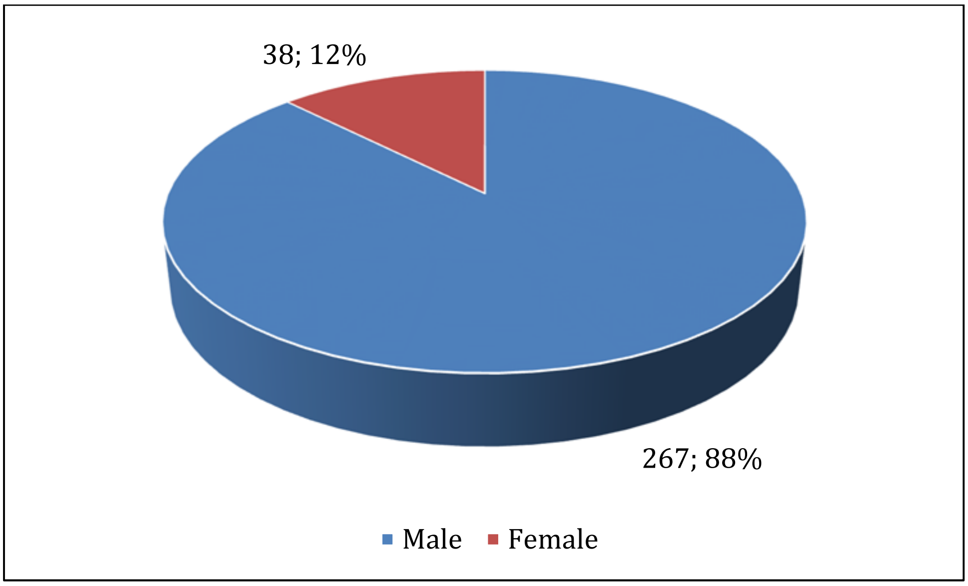


Fig. 4 Gender ratio (Source: Author)

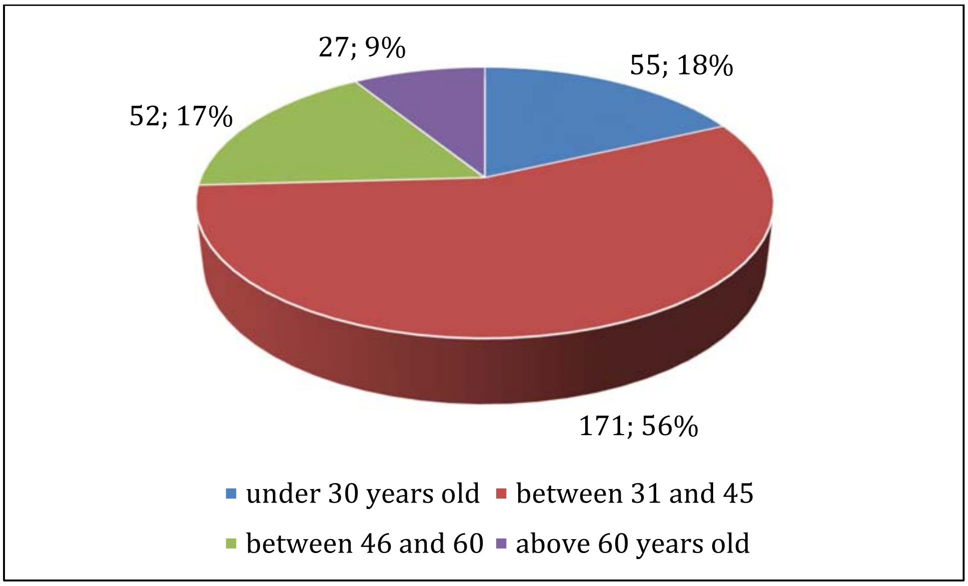


Fig. 5 Age distribution (Source: Author)

The range of annual mileage driven by the participants can be segmented into four categories. The first group includes drivers who drive less than 50,000 km, then those who drive from 50,000 to 100,000 km, following by the group of 100,000 - 200,000 km and those who drive more than 200,000 km. The percentage distribution of driver mileage in the sample is shown in Figure 6.

Vehicle types are classified into six categories: transit bus (city bus for public transport), coach bus (tourist travels), intercity bus (public transport between cities), truck (rigid vehicle), a truck with trailer, and car. The distribution of vehicle categories represented in the sample is shown in Figure 7.

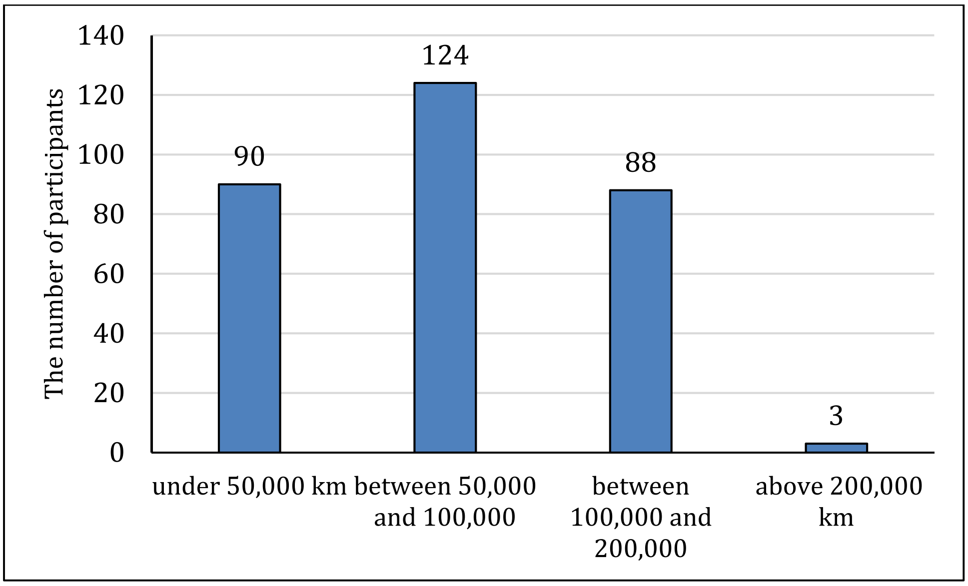


Fig. 6 Annual mileage driven by the participants (Source: Author)

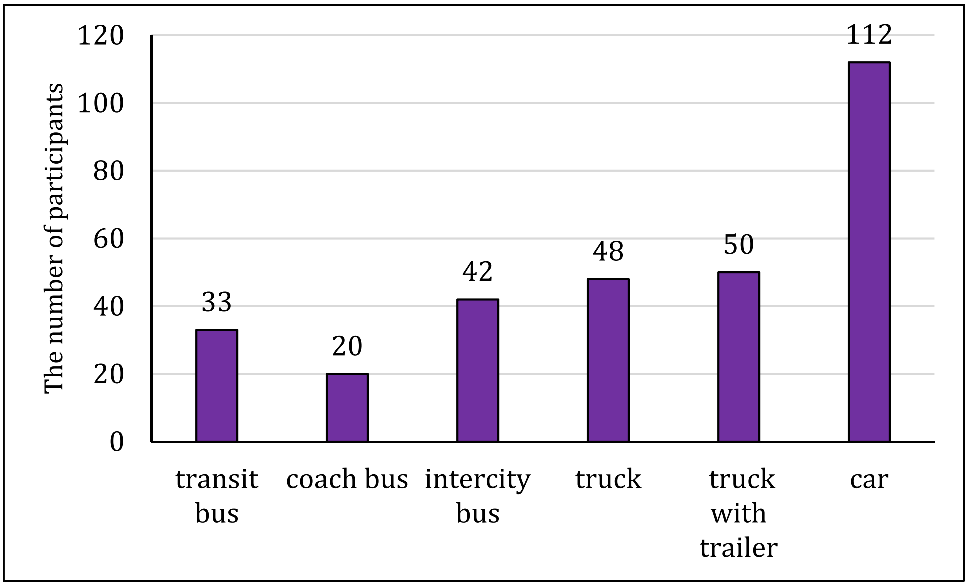


Fig. 7 The distribution of vehicle categories (Source: Author)

When analyzing the period of possession of a driver's license, five categories were formed. These are the periods: up to 5 years, from 6 to 15, from 16 to 25, from 26 to 35 and above 36. The percentage representation of the response categories is given in Figure 8.

When asked how often they drive outside the city, the participants had the opportunity to choose one of the following categories: every day, 3 to 5 times a week, twice a week, once a week, 2 to 3 times a month, once a month or less often. The answers are shown in Figure 9.

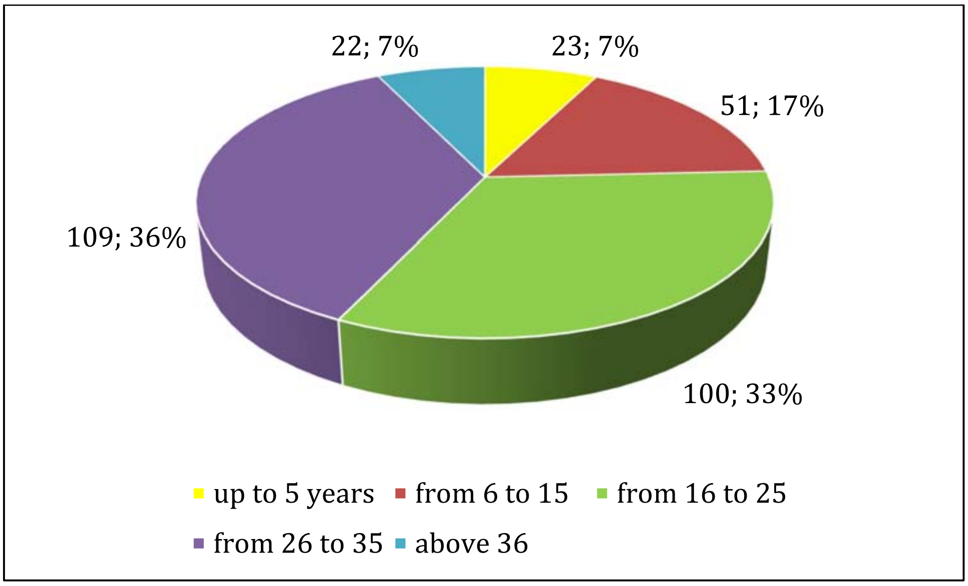


Fig. 8 A period of possession of a driver's license (Source: Author)

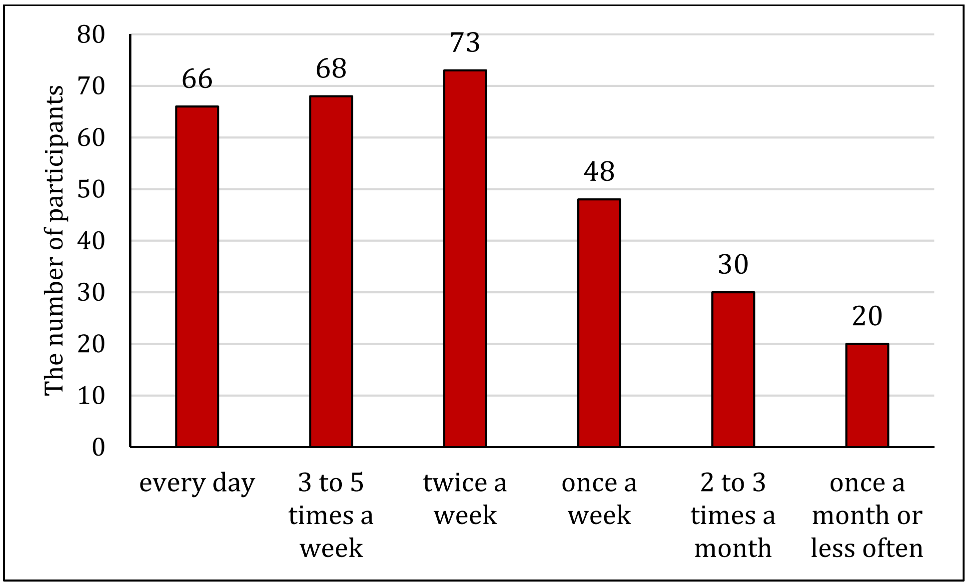


Fig. 9 Frequency of driving outside the city (Source: Author)

The participants were asked to express their opinion about the main cause of road traffic accidents. The possibilities were: human factor, vehicle, road characteristics, environmental issues, something else. As can be seen in Figure 10, the largest number of respondents, 66% of them, identify the human factor as the main factor contributing to the occurrence of RTAs. This is followed by a significantly lower percentage of participants who consider the road to be the main cause of accidents (27%), while a small number of respondents are distributed in other offered categories of answers. Such perceptions related to RTAs are in accordance with the finding in the literature, which is previously stated in the literature review section.

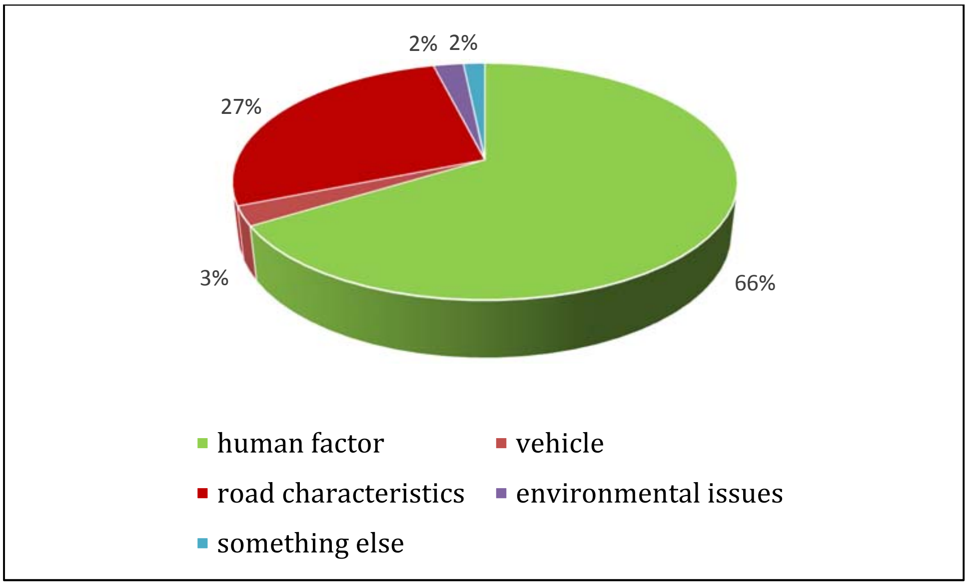


Fig. 10 Main causes of road traffic accidents according to the participants (Source: Author)

The drivers had the task to estimate their maximum driving speed a two-lane rural highway. This is usually a main local road passing through the settlements where the speed limit is 50 km/h and between settlements where the speed limit is from 70 to 90 km/h. Possible answers were: 50, 70, 90, 100 and 120 km/h or more. The distribution of estimates of the maximum speed of own motion is shown in Figure 11.

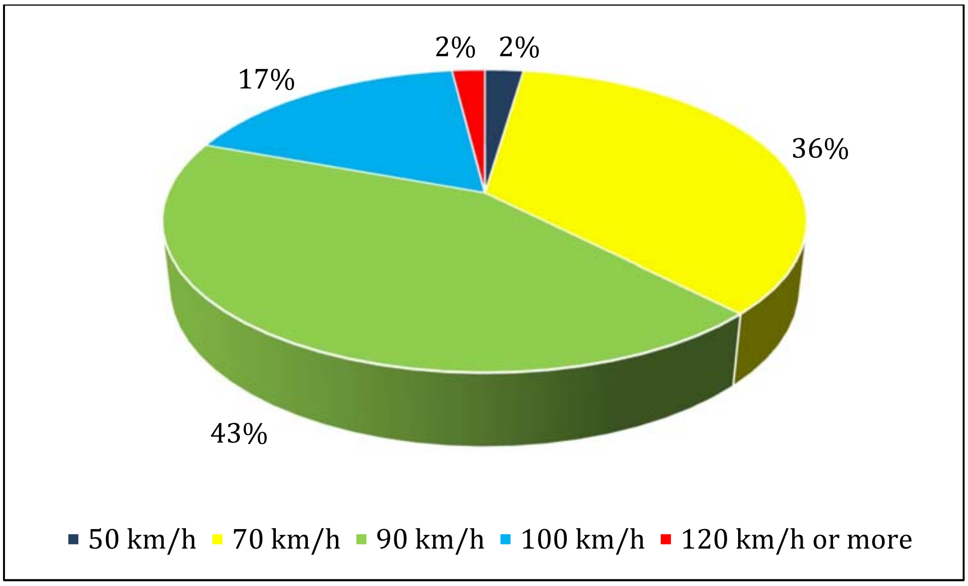


Fig. 11 Self-perceived maximum speed at a two-lane rural highway (Source: Author)

The results show that the largest number of participants distribute their answers in the category of speeds 90 km/h (43% of them). A slightly smaller number of them report that they are moving at a maximum speed of 70 km/h (36%), while around 17% of them opt for a speed of about 100 km/h. An interesting fact to notice here is that a significant violation of the speed limit, which represents driving 120 km/h or more, is reported just by 2% of the participants.

When the participants assessed the driving speed of other drivers in a two-lane rural highway, the same categories were offered: 50, 70, 90, 100, and 120 km/h or more. The percentage of responses is given in Figure 12.

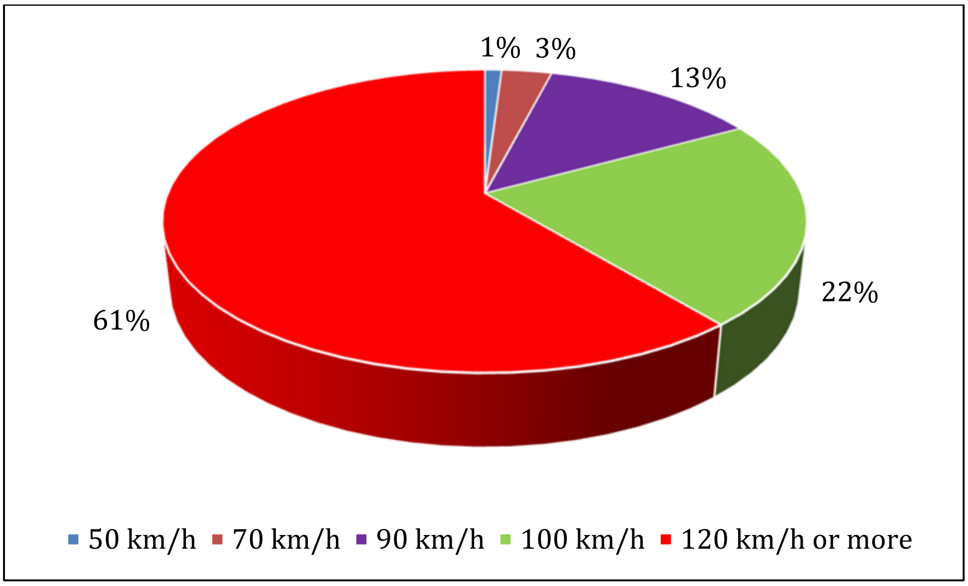


Fig. 12 The assessed maximum speed of others at a two-lane rural highway (Source: Author)

Significantly different answers are observed in the case of estimating the speeds of other drivers on the road. Namely, the largest percentage of respondents estimate that other drivers are moving at a maximum speed of around 120 km/h or more (61%). The next most frequent assessments are around 100 km/h (22%) and 90 km/h (13%).

It is interesting to discuss the answers of the participants regarding the self-assessment of their speed and assessment of other drivers' speed. The existence of a large discrepancy in these two cases is noticeable. It seems that there is a lack of self-critical consideration of participants towards their own speed, as well as a noticeable critical attitude towards the speed of other drivers. Although this may be partially explained by the presence of socially desirable responses, such data are quite worrying considering risk perception on the road. This phenomenon indicates potential directions in terms of creating safety measures in traffic, such as raising driver awareness about a proper observation of their behaviors and actions.

The most important question considering the aims of this dissertation is related to the number of RTAs experienced by participants. They were asked to report just the RTAs with their fault. A concrete number of RTAs that participants from the sample experienced in their driving history is presented in Fig. 13.

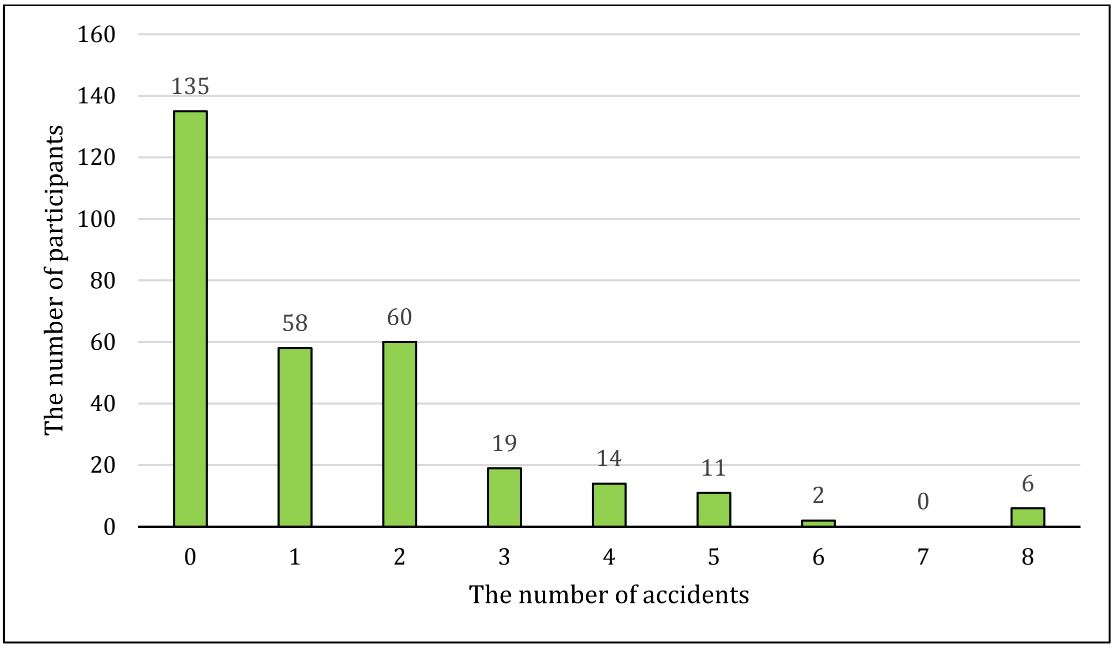


Fig. 13 The number of traffic accidents in the sample (Source: Author)

Further descriptive statistics of the sample is as shown in Table 12. Here, the results from the other four questionnaires (ADBQ, BIS-11, DAQ, Questionnaire for Self-Assessment of Driving Ability) are summarized. In the first column, the scores from each of these questionnaires are considered as input variables; therefore, in the further calculations, they will be marked by x_1 (ADBQ), x_2 (BIS-11), x_3 (DAQ), and x_4 (Questionnaire for Self-Assessment of Driving Ability). On the other hand, as an output, the variable related to the number of RTAs is taken, and accordingly, this variable is marked as y. In the case of x_1, the participants were asked to assess the likelihood of manifestation of aggressive driving using a 6-point Likert scale. Results were given in the range of 1 = never to 6 = almost always. Based on the answers, a score from the ADBQ could range from 20x1=20 to 20x6=120. Accordingly, the domain of this variable is from 20 to 120, as shown in the second column of Table 12. In the same manner, the domains of other variables are determined. The descriptive statistics of the sample shown in Table 12 further relate to the number of participants, minimum, mean, and maximum values of each variable recorded in the considered sample.

Tab. 12 Domain intervals for x_1, x_2, x_3, x_4, and y and descriptive statistics of the sample. (Source: Author)

Variable	Domain	Descriptive statistics of the sample			
		Number of respondents	Minimum	Mean	Maximum
x_1	[20,120]	305	26	49.46	76
x_2	[30,120]	305	49	68.44	86
x_3	[20,100]	305	24	62.52	83
x_4	[22,88]	305	34	66.58	88
y	[0,8]	305	0	1.46	8

5.2 The results of hierarchical regression analysis

To analyze the relationship between experienced traffic accidents and observed characteristics of the driver, the hierarchical regression analysis was conducted (Čubranić-Dobrodolac, Lipovac, Čićević, and Antić, 2017). The statistical procedure was carried out in blocks with control variables the age and driving experience which can affect the overall obtained results. This procedure aims to examine whether the observed characteristics of the driver impacts the propensity toward RTAs, even when the impact of age and driving experience is removed. To determine the assumed impact of control variables on the experience of RTAs, the Pearson correlation coefficients are analyzed firstly (Čabarkapa, Čubranić-Dobrodolac, Čičević, and Antić, 2018). Pearson correlation coefficient can take values from -1 to 1. A positive correlation indicates that if one variable increases, so does the other. Contrary, a negative correlation means that if one variable increases, the other decreases. The size of the absolute value of the coefficient gives information about the strength of the relationship. In the case of perfect correlation, when the coefficient is equal to 1 or –1, one variable can be determined exactly by knowing the value of the other variable. On the other hand, if the coefficient is equal to zero, there is no relationship between the two variables.

In Table 13, a connection between variables age and driving experience with the number of accidents that respondents had in their driving history is shown. Also, Table 13 shows the connection with psychological constructs measured by questionnaires and expressed as total scores. Each of the relations between variables of interest in Table 13 is shown by two parameters. First, the value of the Pearson correlation coefficient is given, and below it is a significance level (p), which should be less than 0.05 to be considered as statistically significant. Even stronger statistical significance is demonstrated if p is lower than 0.01.

Here it is possible to observe the existence of a significant connection of medium intensity between age and driving experience with involvement in traffic accidents. Since the statistically significant correlations were identified in this analysis, the variables age and driving experience are defined as control variables in constructing the regression model of drivers' behavior. This means that the intention is to remove the impact of these two variables in order to conclude about the concrete impact of psychological instruments on the occurrence of RTAs. The correlation coefficients between psychological constructs and traffic accidents will be used to further discuss the obtained results of implemented models.

Tab. 13 Pearson correlation coefficients (Source: Author)

Variable	1	2	3	4	5	6	7
1. Age	-						
Sig.(2-tailed)							
2. Driving experience	.354**	-					
Sig.(2-tailed)	.000						
3. Involvement in traffic accidents	.365**	.375**	-				
Sig.(2-tailed)	.000	.000					
4. ADBQ	.118*	.173**	.521**	-			
Sig.(2-tailed)	.039	.002	.000				
5. BIS-11	.219**	.241**	.546**	.270**	-		
Sig.(2-tailed)	.000	.000	.000	.000			
6. DAQ	.032	.180**	.339**	.253**	.189**	-	
Sig.(2-tailed)	.581	.002	.000	.000	.001		
7. Self-assessment	-.051	.065	-.249**	-.115*	-.130*	.008	-
Sig.(2-tailed)	.379	.258	.000	.045	.023	.894	

* p <.05, ** p <.01

5.2.1 Application of hierarchical regression analysis in the prediction of traffic accidents considering drivers impulsivity (Regression model I)

To create the behavior pattern I, in the first block of hierarchical regression analysis the total number of RTAs that drivers experienced during their driving history was set as a dependent variable. At the same time, the variables age and driving experience were introduced as independent variables. In the second block of hierarchical regression analyses, the achieved overall score from the BIS-11 questionnaire is included as the next independent variable. The implemented *IBM SPSS Statistics* software generated Tables 14, 15, and 16 as outputs of the Regression model I.

In this regression model (Regression model I), the variables age and driving experience, included in the first block, explain 17.4 % (Table 14) of the variance in the occurrence of RTAs ($F(2, 302) = 31.729$, $p < .001$). After the introduction of impulsiveness (Table 14), the regression model describes 38.3 % of the observed variance ($F(3, 301) = 62.192$, $p < .001$), which can be seen from Tables 14 and 15. By analyzing the results from Table 14, the part related to Change Statistics, the impulsiveness through the overall obtained score explains an additional 20.9 % of the variance of the number of experienced RTAs, even when the detected impact of age and driving experience is statistically removed ($F(1, 301) = 101.912$, $p < .001$). The value p is related to the significance of the conclusion and in the statistics theory is generally accepted that if p is smaller than 0.05, the result is considered to be statistically significant. The values of F indicate that this model significantly improves an ability to predict the dependant variable.

To improve the assessment of the obtained model, an analysis of the statistical significance of the model indicators was conducted by ANOVA, which represents the testing of the null hypothesis that R^2 in the population is equal to 0. The obtained results are shown in Table 15. The variable impulsiveness gives a statistically significant unique contribution to this equation and further relationship is described by the following coefficients: $\beta = 0.477$, $t = 10.095$, $p < .001$ (Table 16). By conducting the t-test we can conclude about the significance of the beta coefficient. Since the p-value is lower than 0.05, this means the beta coefficient is statistically significant. Further, the smaller the value of p and the larger the value of t brings to the greater contribution of a considered predictor.

Tab. 14 Summary of the Regression model I (Source: Author)

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics				
					R^2 Change	F Change	df1	df2	Sig. F change
1	.417[a]	.174	.168	.65289	.174	31.729	2	302	.000
2	.619[b]	.383	.377	.56525	.209	101.912	1	301	.000

a. Predictors: (Constant), Driving experience, Age
b. Predictors: (Constant), Driving experience, Age, BIS-11 total

Tab. 15 Examination of the significance of the whole model I using the ANOVA test (Source: Author)

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	27.051	2	13.525	31.729	.000[a]
Residual	128.733	302	.426		
Total	155.784	304			
2 Regression	59.612	3	19.871	62.192	.000[b]
Residual	96.171	301	.320		
Total	155.784	304			

a. Predictors: (Constant), Driving experience, Age
b. Predictors: (Constant), Driving experience, Age, BIS-11 total

Tab. 16 Coefficients of the Regression model I (Source: Author)

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	β		
1 (Constant)	.614	.141		4.343	.000
Age	.129	.037	.190	3.460	.001
Driv. Exper.	.223	.038	.319	5.811	.000
2 (Constant)	-2.611	.342		-7.634	.000
Age	.077	.033	.113	2.347	.020
Driv. Exper.	.159	.034	.227	4.694	.000
Impulsiv.	.052	.005	.477	10.095	.000

The variables Age of the driver and Driving experience, according to the preliminary expectations explain a significant portion of the variance in the occurrence of RTAs. However, the greatest contribution to the explanation of the participation in RTAs in the population is given by the variable Impulsiveness (obtained by the BIS-11 questionnaire), which can be concluded based on the values of the standardized regression coefficient (Table 16).

5.2.2 Application of hierarchical regression analysis in the prediction of traffic accidents considering the aggressiveness of drivers (Regression model II)

In Regression model II a dependent variable was the same as in the previous case (the total RTAs). Age and driving experience as control variables for which the relation with RTAs is previously explained are included in the first block of regression. In the second block, the aggressiveness in driving expressed through the achieved score from ADBQ is included with the aim to explain the importance of aggressive behavior of drivers in the occurrence of RTAs (by the controlling variables age and driving experience). The implemented *IBM SPSS Statistics* software generated Tables 17, 18, and 19 as outputs of the Regression model II.

In this hierarchical regression analysis, the variables age and driving experience, introduced in the first block, as in the model I, explain 17.4 % of the variance in the occurrence of traffic accidents ($F(2, 302) = 31.729$, $p < 0.001$). After the introduction of the ADBQ score in the equation, all variables jointly describe 36 % of the total variance ($F(3, 301) = 56.320$, $p < 0.001$). Driver aggression, seen through the total score on the ADBQ describes the additional 18.6 % of the variance of involvement in traffic accidents ($F(1, 301) = 87.355$, $p < .001$). The results are shown in Table 17 and 18.

Tab. 17 Summary of the Regression model II (Source: Author)

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics				
					R^2 Change	F Change	df1	df2	Sig. F change
1	.417[a]	.174	.168	.65289	.174	31.729	2	302	.000
2	.600[b]	.360	.353	.57575	.186	87.355	1	301	.000

a. Predictors: (Constant), Driving experience, Age
b. Predictors: (Constant), Driving experience, Age, ADBQ total

Tab. 18 Examination of the significance of the whole model II using the ANOVA test (Source: Author)

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	27.051	2	13.525	31.729	.000[a]
Residual	128.733	302	.426		
Total	155.784	304			
2 Regression	56.007	3	18.669	56.320	.000[b]
Residual	99.776	301	.331		
Total	155.784	304			

a. Predictors: (Constant), Driving experience, Age
b. Predictors: (Constant), Driving experience, Age, ADBQ total

Tab. 19 Coefficients of the Regression model II (Source: Author)

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	β		
1 (Constant)	.614	.141		4.343	.000
Age	.129	.037	.190	3.460	.001
Driv. Exper.	.223	.038	.319	5.811	.000
2 (Constant)	-.826	.198		-4.168	.000
Age	.107	.033	.158	3.252	.001
Driv. Exper.	.176	.034	.252	5.165	.000
Aggresiv.	.033	.004	.439	9.346	.000

The values of F indicate that this model also significantly improves an ability to predict the dependant variable. Statistical significance was identified for the variable aggression and it is expressed through the following coefficients: $\beta = .439$, $t = 9.346$, $p <.001$ (Table 19).

5.2.3 Application of hierarchical regression analysis in the prediction of traffic accidents considering the attitudes toward risk propensity of drivers (Regression model III)

A procedure of hierarchical regression analysis in model III is the same as in the previous two cases, as well as the dependent and control variables that are entered into the equation at the beginning. In the second block as an independent variable the overall performance on the Manchester driver attitude questionnaire for risk assessment was considered. The implemented *IBM SPSS Statistics* software generated Tables 20, 21, and 22 as outputs of the Regression model III.

Tab. 20 Summary of the Regression model III (Source: Author)

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics				
					R^2 Change	F Change	df1	df2	Sig. F change
1	.417[a]	.174	.168	.65289	.174	31.729	2	302	.000
2	.502[b]	.252	.245	.62214	.079	31.597	1	301	.000

a. Predictors: (Constant), Driving experience, Age

b. Predictors: (Constant), Driving experience, Age, DAQ total

Tab. 21 Examination of the significance of the whole model III using the ANOVA test (Source: Author)

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	27.051	2	13.525	31.729	.000[a]
Residual	128.733	302	.426		
Total	155.784	304			
2 Regression	39.280	3	13.093	33.829	.000[b]
Residual	116.503	301	.387		
Total	155.784	304			

a. Predictors: (Constant), Driving experience, Age

b. Predictors: (Constant), Driving experience, Age, DAQ total

In the case of Regression model III, the values of the control variables are repeated and explain 17.4 % of the observed variance (F (2, 302) = 31.729, p <0.001). In the second block, by the inclusion of the total risk score from DAQ, all variables define about 25.2 % of the total variance (F (3, 301) = 33.829, p <0.001). As shown in Tables 20 and 21, attitudes toward risk situations, expressed by the total score on the questionnaire describe an additional 7.9 % of the variance of involvement in traffic accidents (F (1, 301) = 31.597, p <0.001). The share of total risk (DAQ) in explaining the variance of RTAs is significantly lower than found for the previously analyzed forms of behavior; however, the values of F indicate that this model also significantly improves an ability to predict the dependant variable. The values which describe the intensity of a relationship are the following: β = .285, t = 5.621, p <.001 (Table 22). A smaller value of β compared to the previous two models indicates that the DAQ instrument contributes less to the explanation of RTAs than BIS-11 or ADBQ.

Tab. 22 Coefficients of the Regression model III (Source: Author)

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	β		
1 (Constant)	.614	.141		4.343	.000
Age	.129	.037	.190	3.460	.001
Driv. Exper.	.223	.038	.319	5.811	.000
2 (Constant)	-.679	.266		-2.548	.011
Age	.133	.035	.197	3.762	.000
Driv. Exper.	.185	.037	.265	4.997	.000
DAQ	.022	.004	.285	5.621	.000

5.2.4 Application of hierarchical regression analysis in the prediction of traffic accidents considering the self-assessment of driving ability (Regression model IV)

In the fourth regression analysis, the dependent variable was the same as in the previous cases (the total number of RTAs). Age and driving experience as control variables are included in the first block of regression. In the second block, the total score of self-assessment of driving ability is included. The aim was to explain the level of the significance of self-assessment that drivers make about their own skills and competencies. The implemented *IBM SPSS Statistics* software generated Tables 23, 24, and 25 as outputs of the Regression model IV.

In the Regression model IV, the variables age and driving experience, introduced in the first block explain 17.4 % of the variance in the occurrence of traffic accidents (F (2, 302) = 31.729, p <0.001). After the score for self-assessment of driving ability is introduced in the equation, the model explains about 24.2 % of the total variance (F (3, 301) = 32.037, p <0.001).

Tab. 23 Summary of the Regression model IV (Source: Author)

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics				
					R^2 Change	F Change	df1	df2	Sig. F change
1	.417[a]	.174	.168	.65289	.174	31.729	2	302	.000
2	.492[b]	.242	.234	.62633	.068	27.155	1	301	.000

a. Predictors: (Constant), Driving experience, Age
b. Predictors: (Constant), Driving experience, Age, Self-assessment of Driving Ability total

Tab. 24 Examination of the significance of the whole model IV using the ANOVA test (Source: Author)

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	27.051	2	13.525	31.729	.000[a]
Residual	128.733	302	.426		
Total	155.784	304			
2 Regression	37.703	3	12.568	32.037	.000[b]
Residual	118.080	301	.392		
Total	155.784	304			

a. Predictors: (Constant), Driving experience, Age
b. Predictors: (Constant), Driving experience, Age, Self-assessment of Driving Ability total

A self-assessment of a driver, considered through the total score on the questionnaire, describes an additional 6.8 % of the variance of involvement in traffic accidents ($F (1, 301) = 27.155$, $p < 0.001$). The results are shown in Tables 23, 24 and 25. It can be concluded that this model also significantly improves the ability to predict the dependant variable. However, the independent variable total score of self-assessment shows a negative relationship: $\beta = -.263$, $t = -5.211$, $p < .001$. The negative values of standardized regression coefficients will be explained in the next subchapter.

Tab. 25 Coefficients of the Regression model IV (Source: Author)

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	β		
1 (Constant)	.614	.141		4.343	.000
Age	.129	.037	.190	3.460	.001
Driv. Exper.	.223	.038	.319	5.811	.000
2 (Constant)	1.677	.245		6.846	.000
Age	.115	.036	.169	3.214	.001
Driv. Exper.	.239	.037	.342	6.474	.000
Self-ass.	-.016	.003	-.263	-5.211	.000

5.2.5 Discussion concerning the results of hierarchical regression analysis

By considering the β coefficients obtained in the hierarchical regression analysis and confirmed by the correlation coefficients from Table 16, it can be noticed that the impact of impulsiveness on the occurrence of RTAs is the highest, followed by aggressiveness (with relatively similar values of β coefficient), while the β coefficients in the case of attitudes toward risk and driving ability self-assessment are considerably lower (with relatively similar values).

The results of hierarchical regression analyses indicate that high scores on the impulsiveness scale BIS-11 and the scale of aggressive behavior in driving ADBQ, form a less safe driving style expressed through a higher probability of experiencing RTAs. Both scales explain a similar proportion of variance in the occurrence of accidents, even when the demographic variables, age and driving experience, are excluded. Although the contribution of all predictors in the hierarchical regression is statistically significant, it may be discussed if their levels are high or low. Here it should be kept in mind that it is difficult to predict some phenomenon based on the psychological instruments, especially if there is a single psychological trait in the model concerning the occurrence of a traffic accident which is a relatively rare event in the driving history of a person. Additionally, besides the stable psychological characteristics of personality and sensory-motor abilities, there are other factors which may affect the occurrence of RTA such as: the current psycho-physical conditions of driver related to stress, fatigue, opiates, then the characteristics of the roads, as well as the characteristics of the vehicle itself that a driver operates. Therefore, the obtained value of R^2 change could be considered as high, especially if it is compared with the results of other relevant studies with a similar methodology where the obtained values are similar or lower (Jiang, Ling, Feng, Wang, & Shao, 2017; Machin, & Sankey, 2008).

Considering BIS-11 and ADBQ, the results can be interpreted through the prism of personality traits and dimensions of behavior that these two instruments estimate and which are similar to a large extent. Thus, it is very difficult to separate the behavioral manifestations of these two phenomena.

When it comes to the instruments for DAQ and self-assessment of driving ability, they have a similar impact on the occurrence of RTAs. A proportion of variance in explanation of the dependent variable is almost identical in both cases. It is important to explain the negative values of standardized regression coefficients for the self-assessment of driving ability instrument. The reason for obtaining such values lies in the fact that good result on the test is related to a good self-assessment of the driving ability which in this case turned out to be a correct measure of safe behavior in traffic reflected through the number of reported RTAs with the fault of the participant.

Considering the predictive power of each of the implemented instruments for the assessment of individual behavior, it is useful to have in mind the results of previous research where scientists used these instruments as a tool for assessment.

First, the BIS-11 instrument is used to assess the impact of general impulsiveness on traffic accidents. It is possible to conclude that this instrument which is often used in the literature, showed a surprisingly high level of predictability in the explanation of accidents in the proposed model. This finding is particularly important in the field of traffic psychology where the stable dispositions of personality, especially in the past, rarely appeared as a reliable indicator of the occurrence of traffic accidents. Some of the most important results from the research where the BIS-11 instrument was used to predict the behavior of drivers are the following. Dahlen et al. (2005) found a slight association between impulsivity scores and smaller penalties which students get for inappropriate behavior. Then, Ryb, Dischinger, Kufera, & Read (2006) found that higher scores on the questionnaire correlate with the behavior such as not wearing a seat belt in the car, driving under the influence of alcohol, excessive speed, but also with involvement in traffic accidents. This result is in accordance with the findings of this dissertation. The most recent results are presented by Moan, Norström, & Storvoll (2013) who verified previous findings according to which the risky behavior in driving is caused by the increased level of impulsiveness among drivers. On the other hand, some studies failed to find such a stable link between impulsiveness and risky behavior in traffic (Jakubczyk, Klimkiewicz, Wnorowska, Mika, Bugaj, Podgórska, Barry, Blow, Brower, & Wojnar, 2013; Xu, Li, & Jiang, 2014).

Considering the Regression model II, which indicates a good predictive power of ADBQ questionnaire for evaluation of aggressive driving behavior, it is possible to conclude that the construction of this model offers a significant result. This result could lead to the introduction of this relatively new instrument, or some similar which examine the same tendencies in driver behavior, in various fields of application such as testing the drivers, their training, selection of professional drivers, and even special programs for drivers temporarily deprived of driving license. The regression model II is supported by the results of similar studies related to the consideration of aggressiveness in the function of unsafe driving behavior. Most of these studies found that aggressive drivers are prone to risky behavior and lighter or heavier traffic accidents compared to drivers with low aggressiveness. Considering the questionnaires used in these situations it is useful to mention those which showed the greatest predictive character in describing unsafe behavior. The most important results are obtained by the researchers who used the following measuring instruments for the assessment of aggressiveness in driving in general or through a specific dimension in the form of individual items: Driver Behaviour Questionnaire – DBQ (Parker et al. 1998), Driving Anger Expression Inventory – DAEI (Deffenbacher, Huff, Lynch, Oetting, & Salvatore, 2000; Dahlen, Edwards, Tubré, Zyphur, & Warren, 2012), Driver's Angry Thoughts Questionnaire – DATQ (Deffenbacher,

Deffenbacher, Lynch, & Richards, 2003), Driving Anger Scale – DAS (Deffenbacher, Oetting, & Lynch, 1994; Dahlen, Edwards, Tubré, Zyphur, & Warren, 2012), Driver Anger Indicators Scale – DAIS (Zhang, Qu, Ge, Sun, & Zhang, 2017). There is no doubt that aggressiveness in driving is a reliable indicator, even when it is viewed with some caution in the sense of socially desirable responses which are inevitable in survey research.

The Regression model III refers to the identified impact of assessed risk of the driver through the DAQ survey on the occurrence of RTAs. It is possible to conclude that this model for traffic accident prediction does not explain a large share of the total variance of accidents which drivers from the sample experienced, although it proved to be statistically significant. This finding could be interpreted by an intuitive character of items in this questionnaire which in some way suggest a research purpose to subjects, thereby increasing the likelihood of socially desirable responding. The DAQ questionnaire in other studies showed a greater predictive power when indicating the gender differences in the attitudes toward risk (Parker et al. 1998). Such an analysis in the observed sample is not reasonable due to the disproportionate presence of drivers of both genders in a sample of professional drivers. Some authors even used the isolated dimensions of this questionnaire, such as speeding, for assessment of implicit attitudes towards risky driving (Rusu, Sârbescu, Moza, & Stancu, 2017). However, the DAQ questionnaire turned out to be an important instrument in predicting RTAs which is proven by examples in the literature (Parker et al., 1998; Taylor, Lynam, & Baruya 2000).

The last analyzed model IV describes the occurrence of RTAs by a driver depending on the reported assessment of their own skills and competencies necessary to operate the vehicle in the Questionnaire for self-assessment of driving ability. Other authors, for example, Tronsmoen (2010), obtained more significant association between the occurrence of accidents and scores from the questionnaire of self-assessment of driving ability; however, the sample was made up exclusively of young novice drivers whose specific driving skills play a crucial role in the traffic accidents occurrence. However, the results of the regression model IV indicate that this instrument is also useful to use for explaining the driver's involvement in RTAs, since the parameters of the model show a statistically significant impact.

When comparing the obtained results with other studies that considered different influencing factors in the field of traffic safety, it can be concluded that the proposed variables in this dissertation showed remarkable results. Namely, if the values of R^2 change are considered, in this research the following values are obtained: .209; .186; .079; .068, which makes an average of .14. Other studies achieved similar or lower values; for example, an average R^2 change is .10 in Swann, et al. (2017); .15 in Yang et al. (2018); .04 in Buckley et al. (2018); .15 in Antoniazzi, & Klein (2019). This confirms that the chosen psychological instruments are proven to be very relevant for RTAs prediction.

5.3 The results of binary logistic regression

To test the cognition about the impact of psychological characteristics on the occurrence of RTAs in some other way, by a differently structured independent variable, a binary logistic regression is applied. The dichotomous dependent variable is related to the (non)participation in RTAs reported by the drivers in the questionnaire. The first category includes the respondents who had not experienced accidents in their driving history, while the second category concerns drivers who reported accidents (regardless of the number). The scores obtained from four instruments for assessing driving behavior and personality traits (DAQ, BIS-11, ADBQ, and Self-Assessment of Driving Ability) are used as independent predictor variables in the analysis. The implemented *IBM SPSS Statistics* software generated Tables 26, 27, and 28 as outputs of the binary logistic regression.

Tab. 26 The Omnibus tests of model coefficients (Source: Author)

		Chi-square	df	Sig.
Step 1	Step	125,711	4	.000
	Block	125,711	4	.000
	Model	125,711	4	.000

Step 1 represents the model where all four considered independent variables are entered together. This step calculates if the model better predicts the dependant variable in a statistically significant manner, compared to the null model with no predictors. In this case, there is just one step (this is the reason why Step, Block, and Model are the same); however, if the procedure is done stepwise or by using blocking of variables, more steps are possible.

First, the chi-square statistic and its significance level are examined. The significance is compared with a critical value, usually .05 or .01 to determine if the overall model is statistically significant. In this case, the model is statistically significant because the significance parameter is less than .001. By *df* is marked the number of degrees of freedom for the model., where one degree of freedom is for each predictor in the model.

Further important information can be found in Table 27. It confirms that the model makes a difference between the drivers who experienced RTAs and the ones who did not, and makes a correct classification in 77.4 % of cases.

Tab. 27 Classification table (Source: Author)

Observed			Predicted		
			RTAs		Percentage correct
			No	Yes	
Step 1	RTAs (yes vs. no)	No	102	33	75.6
		Yes	36	134	78.8
	Overall percentage				77.4

From Table 28 it can be concluded that the variables which significantly contribute to the predictive power of the model are those related to DAQ, ADBQ, and BIS-11, while the instrument for self-assessment of driving ability does not show a statistically significant contribution to the model.

Tab. 28 Variables in the binary logistic regression equation (Source: Author)

Variable	B	Sig	Exp(B)	95% C.I.for EXP(B)
ADBQ	1.427	.000	4.168	2.559 to 6.787
BIS-11	1.782	.000	5.941	3.245 to 10.877
DAQ	1.008	.000	2.740	2.080 to 4.470
Self-assessment	-.223	.395	1.250	.747 to 2.092

B coefficients (denoted as β in the methodological part) give the information about a relationship between the independent variables and the dependent variable, having in mind that the dependent variable is on the logit scale. A value of the coefficient indicates the amount of increase or decrease, depending on the sign of the coefficient, in the predicted log odds of RTAs = 1 (participation in RTAs) that would be predicted by a 1 unit increase or decrease in the predictor, holding all other predictors constant. In the concrete case, the β coefficients are positive for all the instruments except for the instrument that measures self-assessment of driving ability, which is in line with the results obtained in the previous subsection dealing with the hierarchical regression analysis. The negative B coefficient indicates that increasing the value of an independent variable (a higher self-assessment score) results in a reduction of the probability of experiencing RTAs. If the statistical significance is not confirmed for a certain independent variable, this means that the corresponding coefficient is not significantly different from 0.

Because the considered coefficients are in log-odds units, it is not easy to interpret them; therefore, they are usually converted into odds ratios, which are in Table 28 marked as Exp(B). In the concrete case, these odds ratios indicate the following:

- If there is an increase in one unit of the overall aggressiveness score, then the odds will increase 4.168 times. Since the value of odds ratios is greater than 1, this means that the probability that a person had experienced RTAs will also be increased by Eq. (1),
- If there is an increase in one unit of the overall impulsiveness score, then the odds will increase 5.941 times. Since the value of odds ratios is greater than 1, this means that the probability that a person had experienced RTAs will also be increased by Eq. (1), and
- If there is an increase in one unit of the overall DAQ score, then the odds will increase 2.74 times. Since the value of odds ratios is greater than 1, this means that the probability that a person had experienced RTAs will also be increased by Eq. (1).

In general, the proposed model that uses a binary logistic regression shows a high predictive power. It points out that the model with all the previously discussed predictors, except self-assessment of driving ability, is very effective in predicting RTAs. In addition to the statistical significance of the model which certainly represents a relevant indicator of the model's strength, a high percentage of drivers with accidents are detected successfully. This analysis enabled an adequate prediction of the potential number of RTAs which may be expected from the driver based on the scores on the questionnaires.

The main conclusion of performing the hierarchical regression analysis and binary logistic regression is that there is no need to structure the dependent variable in a dichotomous way (because in this case one of the independent variables did not show a statistical significance), but it is better to consider the number of RTAs as the real number (scale variable) in the way as reported by the participants. This conclusion is further used in the modeling of driver behavior by fuzzy logic.

5.4 Modeling driver propensity for traffic accidents by a fuzzy logic approach

Since two general approaches for data processing are statistic and fuzzy approach, in this section the implementation of fuzzy inference systems for modeling driver behavior will be explained. The result of the modeling process will be the proposal of a model that can provide information about driver propensity for traffic accidents, based on the scores obtained from four psychological instruments. The modeling process consists of testing various structures of fuzzy inference systems (FISs) to select the one that produces the minimum amount of error in the description of data. Finally, the selected FIS will be compared with the results of statistical analyses; in this case with multiple regression analysis.

5.4.1 The variables description

To define the variables of FISs, in the modeling process the score from the ADBQ was taken as variable x_1. This variable was named *Aggressiveness* in the programming code. The possible values that variable x_1 can take are from 20 to 120. However, when examining the values of ADBQ scores from the sample of 305 drivers, the minimum value was 26 and the maximum was 76. Therefore, the scores below 26 belong to the fuzzy set for very low aggressiveness (VLA) with the value of membership function equal to 1 ($\mu(x) = 1$). Conversely, scores above 76 are in the fuzzy set for very high aggressiveness (VHA), also with the value of membership function equal to 1. The average value of all ADBQ scores from the sample was close to 49 (Table 12). Therefore, this value was taken as the highest membership function value ($\mu(x) = 1$) in the fuzzy set for medium aggressiveness (MA). The remaining two fuzzy sets, low aggressiveness (LA) and high aggressiveness (HA) were defined in the middle between the limit values and medium value, as shown in Figure 14. The bound values for each of the MFs are determined at the value on the x-axis where the neighboring MFs have the highest membership function value ($\mu(x) = 1$). For example, if the MA is considered, its lower bound is at the point where LA has the value $\mu(x_1) = 1$, and its upper bound is at the point where HA has the value $\mu(x_1) = 1$. The same logic was used to define other input variables. The domains and descriptive statistics for the scores achieved by respondents are shown previously in Table 12.

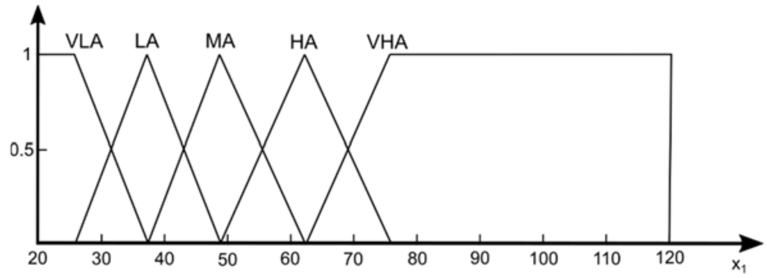


Fig. 14 Input variable x_1 – Aggressiveness (Source: Author)

Variable x_2 represents a score obtained from the BIS-11. This instrument is used for the assessment of impulsivity while driving; therefore, this variable was named *Impulsiveness* in the programming code. Variable x_2 is described by the following fuzzy sets: very low impulsiveness (VLI), low impulsiveness (LI), medium impulsiveness (MI), high impulsiveness (HI), and very high impulsiveness (VHI). The shape and disposition of membership functions for variable x_2 are shown in Figure 15.

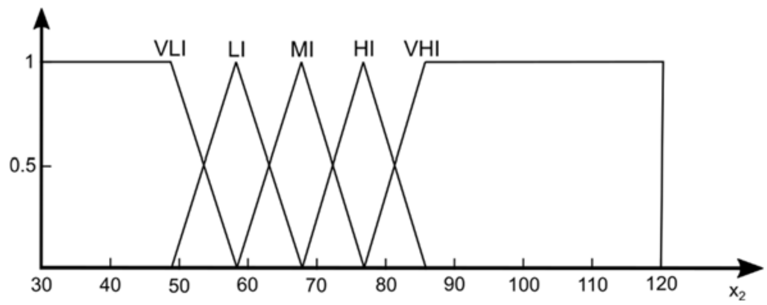


Fig. 15 Input variable x_2 – Impulsiveness (Source: Author)

Variable x_3 relates to the score obtained on the Manchester DAQ. The variable x_3 is named *Risk* in the programming code. Variable x_3 is described by the following fuzzy sets: very low risk (VLR), low risk (LR), medium risk (MR), high risk (HR), very high risk (VHR). The shape and disposition of membership functions for variable x_3 are shown in Figure 16.

Variable x_4 is based on the score obtained from the Questionnaire for Self-assessment of Driving Ability. Variable x_4 is described by the following fuzzy sets: very low self-assessment (VLS), low self-assessment (LS), medium self-assessment (MS), high self-assessment (HS), and very high self-assessment (VHS). The shape and disposition of membership functions for variable x_4 are shown in Figure 17. The variable x_4 is named *Self-assessment* in the programming code.

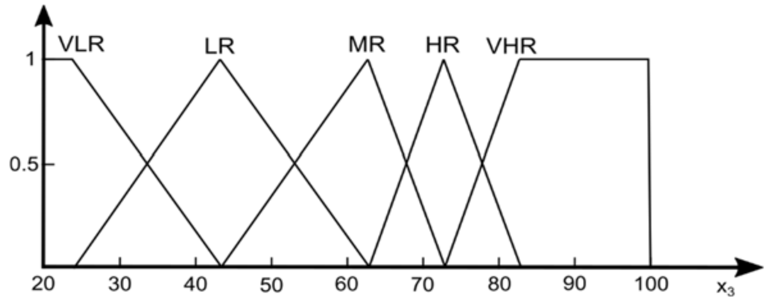


Fig. 16 Input variable x_3 – Risk (Source: Author)

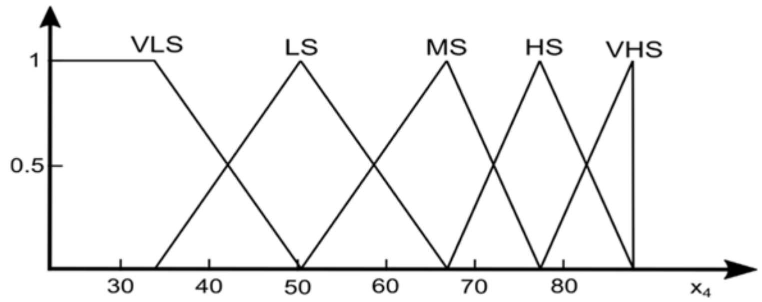


Fig. 17 Input variable x_4 – Self-assessment (Source: Author)

The output variable y relates to the number of RTAs experienced by respondents. In the sample, respondents reported the number of accidents from 0 to 8 (Figure 13). To describe the variable y, 7 membership functions were used unlike in the previous cases where 5 membership functions were used even though the domains of input variables cover 100, 90, 80, and 66 points, respectively (Table 12). The domain of output variable y implies 9 points; however, the number of membership functions is increased in this case because the traffic accidents are relatively rare events and the intention was to describe each category of drivers as precise as possible. However, drivers who participated in 6, 7, or 8 accidents were extremely rare and consequently, they were grouped under one membership function. Therefore, the output variable y was defined as shown in Figure 18. The following fuzzy sets were introduced: very small number of accidents (VSNA), small number of accidents (SNA), moderately small number of accidents (MSNA), medium number of accidents (MNA), moderately high number of accidents (MHNA), high number of accidents (HNA), and very high number of accidents (VHNA). The variable y is named *Accidents* in the programming code.

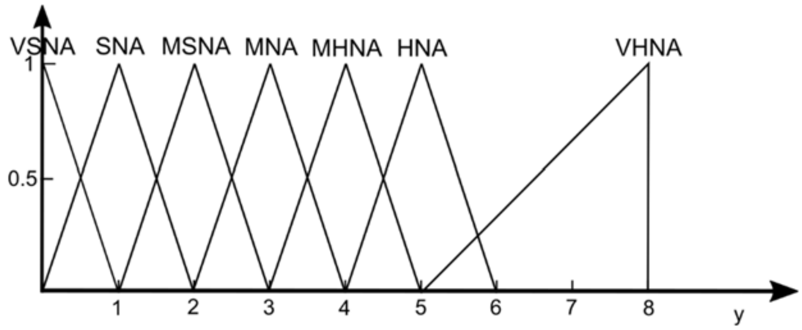


Fig. 18 Output variable *y* – Accidents (Source: Author)

5.4.2 The concept of modeling and fuzzy rules generation based on data

In the modeling process, the described variables x_1, x_2, x_3, x_4, and y were used to form various FIS structures to test which would make the minimum error in the description of the data. Four types of FIS were considered, as follows: one input–one output system, two input–one output system, three input–one output system, and four input–one output system. The concrete FIS concepts to be tested are shown in Table 29. The results of the test should lead to a conclusion as to which psychological instrument, or which combination of two, three, or all four of them, provides the best prediction results regarding driver propensity for traffic accidents.

Tab. 29 Tested fuzzy interference systems (Source: Author)

FIS No.	Used variables	Name of used variable in the programming code
I	x_1, y	Aggressiveness – Accidents
II	x_2, y	Impulsiveness – Accidents
III	x_3, y	Risk – Accidents
IV	x_4, y	Self-assessment – Accidents
V	x_1, x_2, y	Aggressiveness, Impulsiveness – Accidents
VI	x_1, x_3, y	Aggressiveness, Risk – Accidents
VII	x_1, x_4, y	Aggressiveness, Self-assessment – Accidents
VIII	x_2, x_3, y	Impulsiveness, Risk – Accidents
IX	x_2, x_4, y	Impulsiveness, Self-assessment – Accidents
X	x_3, x_4, y	Risk, Self-assessment - Accidents
XI	x_1, x_2, x_3, y	Aggressiveness, Impulsiveness, Risk – Accidents
XII	x_1, x_2, x_4, y	Aggressiveness, Impulsiveness, Self-assessment – Accidents
XIII	x_1, x_3, x_4, y	Aggressiveness, Risk, Self-assessment – Accidents
XIV	x_2, x_3, x_4, y	Impulsiveness, Risk, Self-assessment - Accidents
XV	x_1, x_2, x_3, x_4, y	Aggressiveness, Impulsiveness, Risk, Self-assessment – Accidents

The base of fuzzy rules is essential for the performance of FIS. Here, the well-known approach for defining fuzzy rules proposed by Wang and Mendel (1992) is used. The Wang-Mendel method may be further combined with other optimization algorithms to optimize the FIS structure. For example, Yanar and Akyurek (2011) used simulated annealing metaheuristic to tune a Mamdani-type fuzzy model. In the literature, there are several examples of improvements to the Wang-Mendel method (Gou, Fan, Wang, Luo & Chi, 2016; Gou, Hou, Chen, Wang & Luo, 2015; Lee & Shin, 2003; Wang, 2003; Yang, Yuan, Yuan & Mao, 2010). However, here the original version of this method is used because the purpose of this part of the dissertation is to determine the relationship between the considered instruments. However, the optimization of the FIS structure will be presented in the next Section, where BCO metaheuristic is applied.

As described in detail in the methodology part of this dissertation, the Wang-Mendel method consists of five steps. However, this method will be further explained here, through the implementation in the concrete case, with the data collected in the research related to this dissertation.

Step 1 divides the input and output spaces of the given numerical data into fuzzy regions. Although this study tested 15 FIS structures, and each of them uses different input variables, all the used variables are described in this Section.

Tab. 30 Data set of input and output values (Source: Author)

Respondent	$x_1^{(i)}$	$x_2^{(i)}$	$x_3^{(i)}$	$x_4^{(i)}$	$y^{(i)}$
1	66	76	69	41	8
2	50	60	55	73	0
3	43	62	52	70	0
4	61	76	46	56	3
....	....	....	....	....	....
305	45	75	55	66	3

Step 2 generates fuzzy rules from the collected data. First, our data set was structured as shown in Table 30, where letter i represents one of 305 respondents from the sample. Depending on the chosen FIS, the specific input-output pairs were considered, as shown in Table 31. In the beginning, one data pair was used for the construction of one fuzzy rule. For example, if we consider FIS No. V, the degrees of a given pair $(x_1^{(i)}, x_2^{(i)}; y^{(i)})$ should be determined in different regions. Then, this data pair should be assigned to the regions with a maximum degree. Thus, finally, one fuzzy rule from one pair of desired input-output data was obtained. The IF part was composed of the names of regions with the maximum degree for input variables, and the THEN part from the name of the region with maximum degree for output variables.

Tab. 31 The use of data in a particular fuzzy inference system (Source: Author)

FIS No.	Used input-output data
I	$(x_1^{(1)}; y^{(1)})$, $(x_1^{(2)}; y^{(2)})$,…, $(x_1^{(305)}; y^{(305)})$
II	$(x_2^{(1)}; y^{(1)})$, $(x_2^{(2)}; y^{(2)})$,…, $(x_2^{(305)}; y^{(305)})$
III	$(x_3^{(1)}; y^{(1)})$, $(x_3^{(2)}; y^{(2)})$,…, $(x_3^{(305)}; y^{(305)})$
IV	$(x_4^{(1)}; y^{(1)})$, $(x_4^{(2)}; y^{(2)})$,…, $(x_4^{(305)}; y^{(305)})$
V	$(x_1^{(1)}, x_2^{(1)}; y^{(1)})$, $(x_1^{(2)}, x_2^{(2)}; y^{(2)})$,…, $(x_1^{(305)}, x_2^{(305)}; y^{(305)})$
VI	$(x_1^{(1)}, x_3^{(1)}; y^{(1)})$, $(x_1^{(2)}, x_3^{(2)}; y^{(2)})$,…, $(x_1^{(305)}, x_3^{(305)}; y^{(305)})$
VII	$(x_1^{(1)}, x_4^{(1)}; y^{(1)})$, $(x_1^{(2)}, x_4^{(2)}; y^{(2)})$,…, $(x_1^{(305)}, x_4^{(305)}; y^{(305)})$
VIII	$(x_2^{(1)}, x_3^{(1)}; y^{(1)})$, $(x_2^{(2)}, x_3^{(2)}; y^{(2)})$,…, $(x_2^{(305)}, x_3^{(305)}; y^{(305)})$
IX	$(x_2^{(1)}, x_4^{(1)}; y^{(1)})$, $(x_2^{(2)}, x_4^{(2)}; y^{(2)})$,…, $(x_2^{(305)}, x_4^{(305)}; y^{(305)})$
X	$(x_3^{(1)}, x_4^{(1)}; y^{(1)})$, $(x_3^{(2)}, x_4^{(2)}; y^{(2)})$,…, $(x_3^{(305)}, x_4^{(305)}; y^{(305)})$
XI	$(x_1^{(1)}, x_2^{(1)}, x_3^{(1)}; y^{(1)})$, $(x_1^{(2)}, x_2^{(2)}, x_3^{(2)}; y^{(2)})$,…, $(x_1^{(305)}, x_2^{(305)}, x_3^{(305)}; y^{(305)})$
XII	$(x_1^{(1)}, x_2^{(1)}, x_4^{(1)}; y^{(1)})$, $(x_1^{(2)}, x_2^{(2)}, x_4^{(2)}; y^{(2)})$,…, $(x_1^{(305)}, x_2^{(305)}, x_4^{(305)}; y^{(305)})$
XIII	$(x_1^{(1)}, x_3^{(1)}, x_4^{(1)}; y^{(1)})$, $(x_1^{(2)}, x_3^{(2)}, x_4^{(2)}; y^{(2)})$,…, $(x_1^{(305)}, x_3^{(305)}, x_4^{(305)}; y^{(305)})$
XIV	$(x_2^{(1)}, x_3^{(1)}, x_4^{(1)}; y^{(1)})$, $(x_2^{(2)}, x_3^{(2)}, x_4^{(2)}; y^{(2)})$,…, $(x_2^{(305)}, x_3^{(305)}, x_4^{(305)}; y^{(305)})$
XV	$(x_1^{(1)}, x_2^{(1)}, x_3^{(1)}, x_4^{(1)}; y^{(1)})$, $(x_1^{(2)}, x_2^{(2)}, x_3^{(2)}, x_4^{(2)}; y^{(2)})$,…, $(x_1^{(305)}, x_2^{(305)}, x_3^{(305)}, x_4^{(305)}; y^{(305)})$

In Step 3, a problem of conflicting rules needed to be solved. These are the rules that have the same IF part, but a different THEN part. For this purpose, each of the formed rules should be assigned a degree, defined by Eq. (12) for the case when a rule is defined as follows: "IF x_1 is A and x_2 is B, THEN y is C". In a conflict group, only the rule that has a maximum degree should be accepted.

$$D(Rule) = \mu_A(x_1) * \mu_B(x_2) * \mu_C(y) \tag{12}$$

Step 4 makes a combined fuzzy rule base, which consists of rules obtained from empirical data and linguistic rules acquired from a human expert. Finally, Step 5 determines a mapping from input to output space using a defuzzification procedure. In the dissertation, the results of FIS testing in the case when all FIS structures use just rules from empirical data and the case when all considered FIS structures use a complete rule base are compared. In defining a complete rule base, expert logic was based on the assumption of linear interdependence between input and output variables.

5.4.3 Calculations related to FIS structures and results

This section consists of three parts. In the first part, a detailed procedure for solving a FIS based on empirical data is demonstrated. The second part presents the complete modeling process, in which 15 various FIS are tested. Here, the essence is in the results, not the procedure. Further, in the second part, the results of the FIS (that makes the minimum error in describing the data) are compared with multiple regression analysis. Finally, in the third part a sensitivity analysis of the FIS No. XV based on the sample decomposition is performed.

Demonstration of solving the FIS with two input variables x_1 and x_2

To illustrate the proposed methodology, a detailed description of solving FIS No. V is offered, with corresponding programming code applied in MATLAB.

FIS No. V uses two input variables (x_1 and x_2), which are in the programming code labeled as *Aggressiveness* and *Impulsiveness*, respectively. The output variable y is denoted as *Accidents*.

Because the Wang-Mendel method for the design of the FIS is applied, the previously described five steps were solved in the following way. The input and output spaces of the given numerical data are divided into fuzzy regions (Step 1), as previously explained. The regions are determined by the lower and upper bound of MFs at the x-axis for input variables and y-axis for the output variable (Figures 14, 15, and 18). The variables *Aggressiveness*, *Impulsiveness*, and *Accidents* are shown in Figures 14, 15, and 18, respectively.

Algorithm 1 (Figure 19) prepared the data for the realization of Steps 2 and 3. The main aim here is to obtain the values in the matrix Membership Functions Product (*MFPROD*). In this case, this matrix has four columns. The first column represents the product of values of membership functions of the regions with the maximum degree, both for input and output variables. This value is a prerequisite for the implementation of Step 3 because it practically represents the value of *D(Rule)* from Eq. (12). The second, third, and fourth columns denote the region with a maximum degree for *Aggressiveness*, *Impulsiveness,* and *Accidents*, respectively. This information is essential for the implementation of both Step 2, to generate all possible 305 fuzzy rules, and Step 3, to reduce these rules to the appropriate number.

After the creation of 305 fuzzy rules, there were many same rules in the base. To resolve this problem, Algorithm 2 (Figure 20) was implemented. In the case of FIS No. 5, after excluding the same fuzzy rules, there were 53 remaining. By implementing the proposed programming code, the remaining rules could be found in the matrix *MFPRODfin*.

```
MFPROD=zeros(length(Aggressiveness),4);
for j=1:length(Aggressiveness)
    a = Aggressiveness(j);
    i = Impulsiveness(j);
    n = Accidents(j);
    amax = [];
    imax = [];
    nmax = [];
    for c=1:length(Propensity.input(1).mf)
        amax                                  =                                  [amax
evalmf(a,Propensity.input(1).mf(c).params,Propensity.input(1).mf(c).type)
];
    end
    for d=1:length(Propensity.input(2).mf)
        imax                                  =                                  [imax
evalmf(i,Propensity.input(2).mf(d).params,Propensity.input(2).mf(d).type)
];
    end
    for f=1:length(Propensity.output.mf)
        nmax                                  =                                  [nmax
evalmf(n,Propensity.output.mf(f).params,Propensity.output.mf(f).type)];
    end
    [mfa,ida] = max(amax);
    [mfi,idi] = max(imax);
    [mfn,idn] = max(nmax);
    EVAL(j,1)=mfa;
    EVAL(j,2)=mfi;
    EVAL(j,3)=mfn;
    MFPROD(j,1)=EVAL(j,1)*EVAL(j,2)*EVAL(j,3)
    MFPROD(j,2)=ida
    MFPROD(j,3)=idi
```

Fig. 19 Algorithm 1 – Determination of regions with a maximum degree (Source: Author)

Among 53 rules, there were certain conflict rules with the same IF part and a different THEN part. According to the procedure described in Step 3 of the Wang-Mendel method, Algorithm 3 (Figure 21) was proposed. The final fuzzy rule base was set in the matrix *Drules*, that is in the matrix *Dsort* where all the rules are sorted from lower to higher values of the first input variable, and afterward of the second. In the case of FIS No. V, there were 18 fuzzy rules obtained from the collected data.

```
MFPRODnew=MFPROD;
for k=1:size(MFPROD,1)
   H=zeros(length(Aggressiveness),1);
   for g=1:size(MFPROD,1)
     X(g,1)=MFPROD(k,2)==MFPROD(g,2)   &   MFPROD(k,3)==  MFPROD(g,3)   &
MFPROD(k,4)== MFPROD(g,4);
     H(g,1)=X(g,1)*g;
     VMF(g,1)=X(g,1)* MFPROD(g,1);
     MMAX=max(VMF);
   end
   S=nonzeros(H);
   MFPRODnew(S,1)=MMAX;
end
MFPRODfin=unique(MFPRODnew,'rows','stable')
```

Fig. 20 Algorithm 2 – Reducing the same rules (Source: Author)

```
D=MFPRODfin;
for k=1:size(D,1)
H=zeros(size(D,1),1);
  for g=1:size(D,1)
     Y(g,1)=D(k,2)==D(g,2) & D(k,3)==D(g,3);
     H(g,1)=Y(g,1)*g;
     VVMF(g,1)=Y(g,1)*D(g,1);
     [MMAX,idMMAX]=max(VVMF);
   end
   H(idMMAX,1)=0;
   Hfin=nonzeros(H);
   D(Hfin,:)=0;
end
B=zeros(size(D,1),length(Propensity.input)+2);
Drules = setdiff(D,B,'rows','stable')
Dsort = sortrows(Drules,[2 3])
```

Fig. 21 Algorithm 3 – Reducing the conflict rules (Source: Author)

According to Step 4, the final rule base was formed and missing rules were added based on human expert opinion. In this procedure, the assumption that there was a linear interdependence between input and output variables is applied; for example, if the aggressiveness is higher, the number of accidents experienced by a driver should be higher. Accordingly, the final fuzzy rule base of FIS No. V containing 25 rules is shown in Table 32. Note that the rules written in *Italic* are proposed by the authors and the other 18 rules are obtained from the empirical data.

Tab. 32 Final fuzzy rule base of fuzzy inference system No. V (Source: Author)

x_1	**VLA**	*VSNA*	VSNA	MSNA	*SNA*	*MSNA*
	LA	VSNA	VSNA	VSNA	MNA	SNA
	MA	VSNA	VSNA	MSNA	VHNA	VSNA
	HA	MSNA	VSNA	SNA	MHNA	*MNA*
	VHA	*SNA*	*MSNA*	MSNA	MHNA	*HNA*
		VLI	**LI**	**MI**	**HI**	**VHI**
		x_2				

Finally, the defined FIS No. V required testing. This was performed based on Eq. (13). Cumulative deviation (*CD*) is a measure that describes how well the FIS describes the empirical data. *CD* was calculated as an absolute value of the difference between the actual number of accidents experienced by drivers in the sample, and the corresponding results of FIS No. V. This calculation of absolute values of differences was completed for each respondent from the sample, meaning that in this case, *CD* is a sum of all 305 deviations. The result of FIS No. V for a respondent number *i* in Eq. (2) is marked as *Propensity(i)*. The same concept of calculating the performance of FIS structures can be found in other papers (see Čubranić-Dobrodolac, Molkova, and Švadlenka, 2019; Čubranić-Dobrodolac, Švadlenka, Čičević, and Dobrodolac, (2020a); Čubranić-Dobrodolac, Švadlenka, Čičević, and Trifunović (2020b); Čubranić-Dobrodolac, Švadlenka, Čićević, Trifunović, and Dobrodolac (2020c); Jovcic, Prusa, Dobrodolac, and Svadlenka, 2019).

$$CD = \sum_{i=1}^{305} \left| y^{(i)} - Propensity(i) \right| \tag{13}$$

The result of the final calculation is presented in Table 33. It is interesting to note that the results of FIS (where fuzzy rules are based only on empirical data) and FIS with complete fuzzy rules base are very similar, and vary in less than 1 % in this case. A comparison of empirical data and results of FIS No. V is presented in Figure 22. It is interesting to compare these results with some other research. For example, in the paper Čubranić-Dobrodolac et al. (2019) a relationship between the assessment of road characteristics and RTAs is examined. These results are presented in Figure 23. By a visual comparison of the results from this dissertation and the results presented in the paper Čubranić-Dobrodolac et al. (2019), a conclusion can be reached that the considered psychological traits explain the occurrence of traffic accidents significantly better compared to the assessment of dangerous places on the road and road characteristics. This can be concluded based on worse matching between the results of FIS describing assessments of road characteristics and empirical data (Figure 23) compared to FIS describing psychological traits (Figure 22); however, also based on the calculated CD values by Eq (13).

Further, it is interesting to compare the results of other FIS structures proposed here, which appears in the next subsection.

Tab. 33 The result of testing the fuzzy inference system No. V (Source: Author)

	FIS No. V (18 fuzzy rules based on data)	FIS No. V (25 fuzzy rules – complete base)
CD	473.5682	473.0376

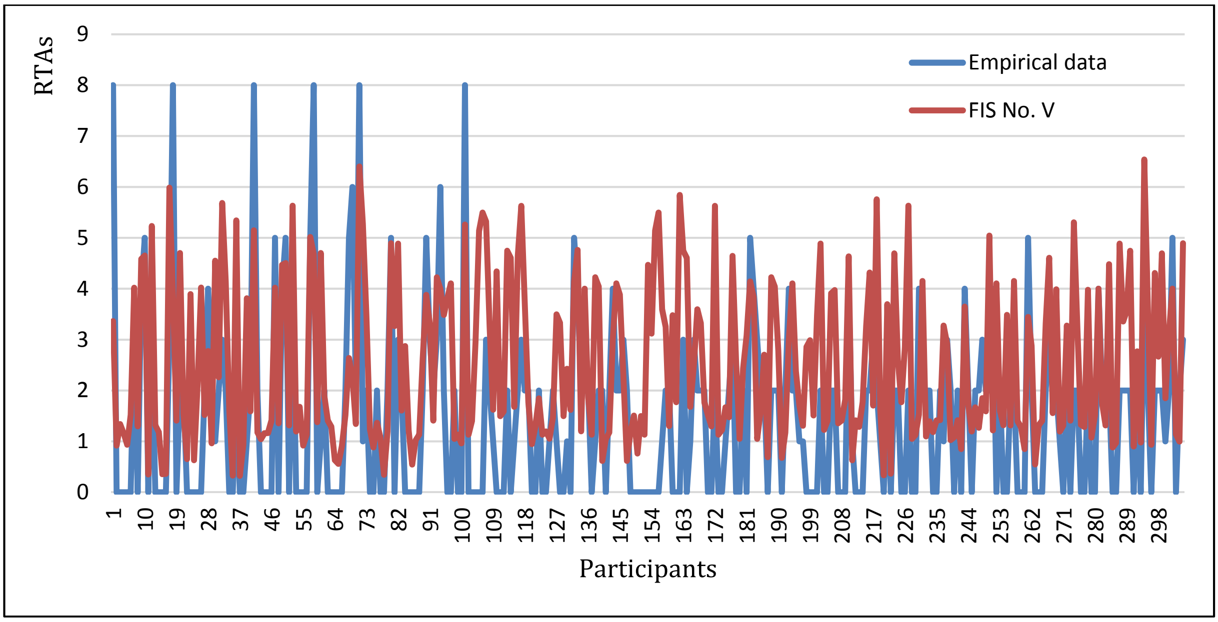


Fig. 22 Comparison of empirical data and results of FIS No. V (Source: Author)

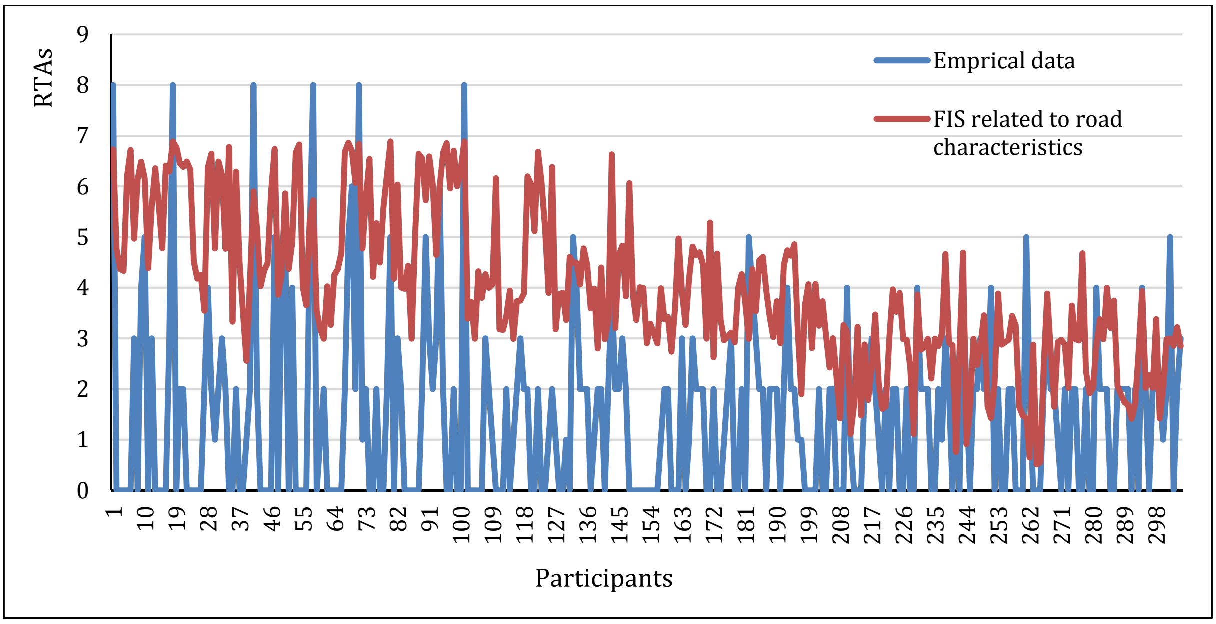


Fig. 23 Comparison of empirical data and results of FIS related to the road characteristics assessments (Source: Author)

Results of all 15 FIS tests and comparison with multiple regression analysis

To achieve one of the aims of this dissertation — to conclude which psychological instruments provide the best assessment of driver propensity for traffic accidents — it is necessary to test all of the proposed 15 FIS structures. This was carried out by the same procedure as previously described in the case of FIS No. V. The proposed programming code was used in all cases; however, certain minor changes were made concerning the used variables and their number.

The results of the testing are shown in Table 34. By comparing the second and third columns, it is evident how many fuzzy rules were obtained from the empirical data compared to the complete fuzzy rule base. Further, the results of testing various FIS structures in two cases where the FIS was designed only from fuzzy rules from the empirical data, and where there is a complete fuzzy rule base, are presented in the fourth and fifth columns, respectively. Even though the results in these columns are very similar, there are certain cases where the complete fuzzy rules base provides worse results. This means there is a space for optimization of the fuzzy rules base; however, this is not a topic of interest here. The general conclusion from this research is that driver propensity for traffic accidents can be modeled in the best way by using all four considered psychological instruments.

Tab. 34 Results of all 15 FIS structures testing (Source: Author)

FIS No.	Number of rules obtained from empirical data	Number of rules in the complete fuzzy rule base	*CD* when FIS uses just fuzzy rules from empirical data	*CD* when FIS uses the complete fuzzy rule base
I	5	5	397.3646	397.3646
II	5	5	584.1899	584.1899
III	5	5	365.4782	365.4782
IV	5	5	402.1822	402.1822
V	18	25	473.5682	473.0376
VI	19	25	329.0113	327.1454
VII	21	25	350.2779	349.0564
VIII	17	25	323.3962	324.5296
IX	19	25	306.4532	306.8304
X	20	25	376.0972	378.7192
XI	45	125	344.9796	343.0711
XII	55	125	313.9698	318.7048
XIII	50	125	354.7903	359.2937
XIV	47	125	329.1417	329.7905
XV	101	625	299.7392	305.8853

Finally, the FIS that shows the best performance should be compared with the results of statistical analyses, in this case with multiple regression analysis. The results from tests with the same data using multiple regression analysis are described in detail in the paper by Čubranić-Dobrodolac et al. (2020a). However, the essential aspect of this paper, which is important for the purpose of comparison, is as follows. A set of data may be described by Eq. (3) in the case of multiple regression analysis, as explained in the methodology part of the dissertation; however, in the concrete case, Eq. (14) is valid.

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 \tag{14}$$

where y and x_n are variables that mark the same as in the FIS structures, i.e. y is Accidents, x_1 is Aggressiveness, x_2 is Impulsiveness, x_3 is Risk, and x_4 is Self-assessment. b_1, b_2, b_3, and b_4 are the corresponding regression coefficients, and b_0 is the intercept.

After the necessary calculations, the results are as follows: b_0 = - 2.770, b_1 = 0.023, b_2 = 0.039, b_3 = 0.013, and b_4 = - 0.011. Based on the formed regression equation, and by testing this using Eq. (3), the CD value is 326.7150. The results of testing the FIS structures and multiple regression analysis are shown jointly in Figure 24. As is evident, FIS No. XV offers the minimum error in the description of data, which makes it the currently best-found decision-making tool in assessing the driver propensity for traffic accidents.

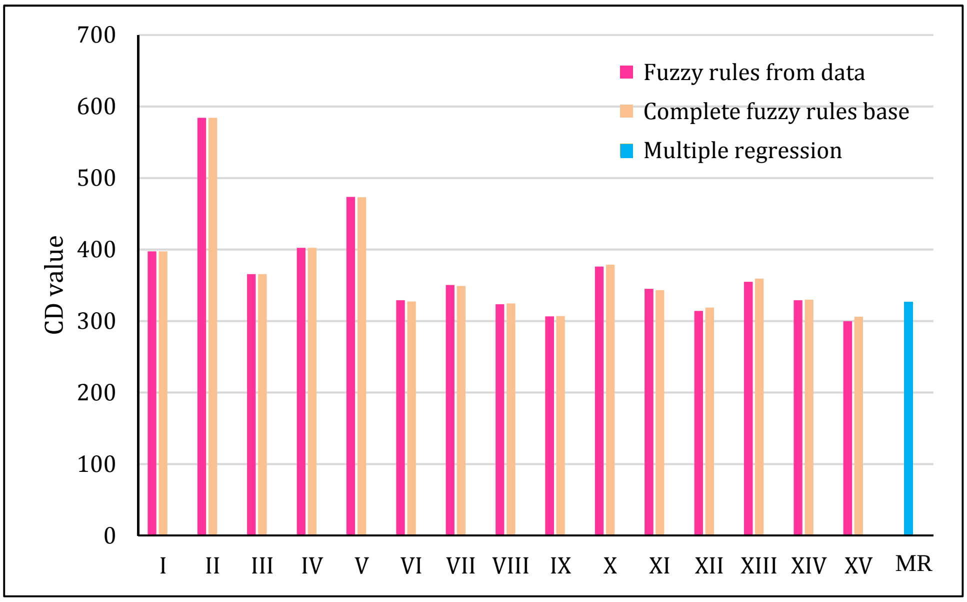


Fig. 24 Comparison of results of the FIS structures and multiple regression analysis (Source: Author)

Sensitivity analysis of the FIS No. XV based on the sample decomposition

Because the FIS No. XV was determined as the best of the analyzed FIS structures, it is interesting to perform a sensitivity analysis considering particular groups from the sample. Accordingly, FIS No. XV is tested based on the individual categories considering gender and age. In this procedure, the calculation of cumulative deviation (CD) was slightly different, because the number of respondents differed from group to group. To be able to compare the CD values, the following Eq. (15) was used:

MR

$$CD_g = \frac{n}{k} \times \sum_{i=1}^{k} \left| y^{(i)} - Propensity(i) \right| \tag{15}$$

where CD_g is a cumulative deviation of the considered group, n is the total number of respondents, and k is the number of respondents in the considered group.

Tab. 35 The results of the sensitivity analysis of the FIS No. XV based on the sample decomposition (Source: Author)

FIS No.	*CD* values					
	Gender		Age			
	Female	Male	18–30	31–45	46–60	over 60
I	448.4745	390.3084	365.0573	401.1536	396.7205	439.0159
II	677.1041	571.3622	521.6775	589.0191	568.4074	706.9715
III	511.7653	345.2819	307.2864	374.8513	331.8670	485.2964
IV	487.5104	390.4018	354.1721	402.9592	432.9751	434.5825
V	527.2683	465.5505	431.1230	477.5572	465.6013	541.7410
VI	465.0236	308.1100	294.2280	335.2239	300.9599	391.3869
VII	436.5012	336.9838	360.1556	341.3357	365.3794	343.8167
VIII	461.4502	305.6264	269.9744	321.1395	373.4631	361.3978
IX	332.9108	303.2297	281.4712	304.9135	319.1121	345.4724
X	527.9542	358.1160	357.2947	375.6479	381.4629	434.3549
XI	452.9036	327.9077	298.4880	335.4774	398.5793	373.6620
XII	366.0940	312.1624	281.0126	330.0676	313.9347	332.6145
XIII	482.5661	342.2748	327.6299	342.7775	415.5273	417.3337
XIV	414.9863	318.0284	328.6142	322.7749	355.0851	327.7203
XV	407.1964	291.8982	281.3575	291.1322	378.4428	308.8877

The results of the test procedure are shown in Table 35. It can be noticed that FIS No. XV showed the best performance in three groups: male respondents, respondents aged 31–45, and those aged over 60. However, in the remaining three groups, the number of respondents was relatively small: 12% for the female group, 18% for those aged 18 to 31, and 17% for those aged 46 to 60. To validate the results for smaller groups, the research should be expanded to new respondents of respective groups. Additionally, the implementation of certain methods for FIS structure optimization, such as metaheuristic algorithms, would be welcome.

5.5 Proposal of a Bee Colony Optimization (BCO) based algorithm to improve a fuzzy inference system for driver behavior modeling

This Section aims to further optimize the best-found FIS in previous Subsection 5.4. The optimization here means that the considered FIS should be adjusted to the empirical data. The proposed algorithm based on BCO metaheuristic will be tested in three cases, based on different approaches for the design of an initial FIS. The final aim is to propose a FIS that acts as similar as possible to the pattern formed by real data. Additionally, the aim is to examine how the starting FIS in the optimization procedure affects the quality of the found solution at the end of FIS optimization.

5.5.1 Three approaches to designing an initial fuzzy inference system

There are three different approaches to forming the initial FIS proposed and tested. Let we assume that each input variable *j* is defined by N_j membership functions (MFs) and N_j is an odd number starting from 3. Here the triangular and trapezoidal MFs in describing variables are considered and different approaches just on input variables are applied.

The first approach is based on the symmetrical principle, where MFs are distributed along the entire interval of possible solutions, from I^j_{min} to I^j_{max}, and the axis of symmetry is in the middle of this interval. This method implies the use of triangular MFs and a point with the maximum degree for the central MF (MF *number* $\left\lceil \frac{N_j}{2} \right\rceil$, where MF *number 1* is at the beginning of variable interval) is based on the axis of symmetry. A point with the maximum degree for the MF *number 1* of variable *j* is located at the minimum value of the variable interval (I^j_{min}). On the other hand, a point with the maximum degree for the MF *number* N_j of variable *j* is located at the maximum value of the variable interval (I^j_{max}). The positions of points with the maximum degree for all MFs can be expressed by Eq. (16):

$$P^j MF_i = I^j_{min} + \frac{I^j_{max} - I^j_{min}}{N_j - 1}(i-1), \tag{16}$$

where $P^j MF_i$ is the position of a point with the maximum degree for MF *number i*, for variable *j*.

The second method is based on the asymmetric principle taking the mean value from the empirical sample of considered variable *j* ($\overline{X}_j$) as a point with the maximum degree for the central MF. Therefore, the positions of points with the maximum degree for all MFs can be determined by Eq. (17):

$$P^j MF_i = \begin{cases} I^j_{min} + \dfrac{\overline{X}_j - I^j_{min}}{\left\lceil \frac{N_j}{2} \right\rceil - 1}(i-1), & \forall\, i = 1, 2, .., \left\lceil \frac{N_j}{2} \right\rceil \\ \overline{X}_j + \dfrac{I^j_{max} - \overline{X}_j}{\left\lceil \frac{N_j}{2} \right\rceil - 1}\left(i - \left\lceil \frac{N_j}{2} \right\rceil\right), & \forall\, i = \left(\left\lceil \frac{N_j}{2} \right\rceil + 1\right), .., N_j \end{cases}. \tag{17}$$

The asymmetric principle is also applied in the third method where the mean and extreme values from the empirical sample are taken into account when defining the points with the maximum degrees for MFs *number 1*, $\left\lceil\frac{N_j}{2}\right\rceil$ and N_j. Therefore, in this method, the positions of points with the maximum degree for all MFs can be determined by Eq. (18), where X_{min}^j is the minimum value from the sample for variable *j*, and X_{max}^j is the maximum value from the sample for variable *j*:

$$P^j MF_i = \begin{cases} \left[I_{min}^j, X_{min}^j\right], & i = 1\,,\ I_{min}^j < X_{min}^j \\ X_{min}^j + \dfrac{\overline{X}_j - X_{min}^j}{\left\lceil\frac{N_j}{2}\right\rceil - 1}(i-1), & \forall\, i = 1,2,..,\left\lceil\frac{N_j}{2}\right\rceil \\ \overline{X}_j + \dfrac{X_{max}^j - \overline{X}_j}{\left\lceil\frac{N_j}{2}\right\rceil - 1}\left(i - \left\lceil\frac{N_j}{2}\right\rceil\right), & \forall\, i = \left(\left\lceil\frac{N_j}{2}\right\rceil + 1\right),..,N_j \\ \left[X_{max}^j, I_{max}^j\right], & i = N_j\,,\ X_{max}^j < I_{max}^j \end{cases}. \tag{18}$$

After the variables of FIS are defined, the next step is to determine the fuzzy rules. In all three previously described methods, we use a well-known approach proposed by Wang and Mendel (1992). Finally, when all parameters of FIS are defined, its performance should be tested by the optimization algorithm which will be further explained in subsection 5.5.2. In this process, the objective function can be expressed by Eq. (19):

$$\text{Minimize}\ \ CD = \sum_{z=1}^{PA} \left|y^z - FIS(z)\right| \tag{19}$$

where *CD* is the cumulative deviation between the empirical data and results of created FIS structures during the optimization procedure, *PA* is the number of participants in the sample, y^z is the number of RTAs that participant *z* experienced in the driving history and *FIS(z)* is the result of FIS for the participant *z*. Therefore, the *CD* is a measure that describes how well a FIS describes the empirical data.

5.5.2 Implementation of BCO algorithm and simulation results

In all three approaches, the input variables are described by five MFs. For all input variables, the MFs are described as follows: *very low*, *low*, *medium*, *high,* and *very high* level of the considered variable. For example, the score from the ADBQ gives the information about driver *aggressiveness*; accordingly, five fuzzy sets that describe this input variable are the following: *very low aggressiveness* (VLA), *low aggressiveness* (LA), *medium aggressiveness* (MA), *high aggressiveness* (HA) and *very high aggressiveness* (VHA). The same principle is implemented when the MFs of other variables are named. The BIS-11 test is named *impulsiveness* and the letter "I" is used at the end of the name of MFs, the DAQ is considered as *risk* and the letter "R" is taken, while the Questionnaire for Self-Assessment of Driving Ability is abbreviated as *self-assessment*, hence the letter "S" is used.

Using the first approach, where the input variables are defined based on the symmetry principle, the MFs are distributed as shown in Figure 25. As can be seen, the axis of symmetry is positioned in the middle of the variable domain. In the case of *aggressiveness*, this axis is at point 70, for *impulsiveness* – at point 75, for *risk* – at point 60 and for *self-assessment* – at point 55. To offer more precise information about the position of MFs, the concrete values for which the degree of corresponding MF is equal to 1 are presented in Table 36.

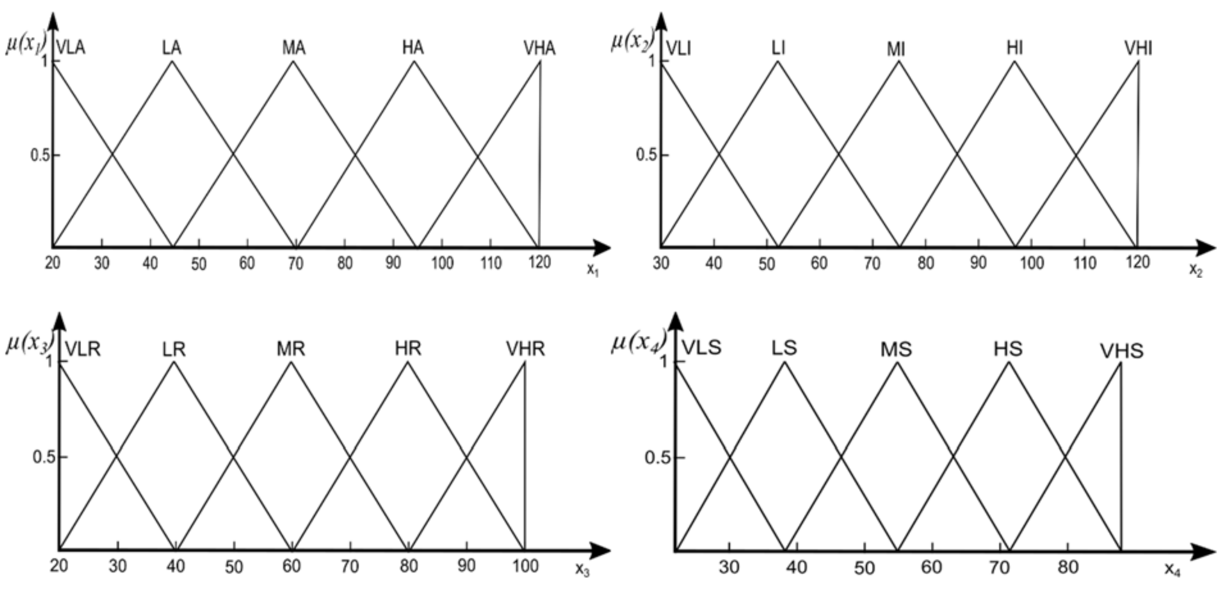


Fig. 25 MFs for input variables defined by the symmetric principle (Source: Author)

Tab. 36 The values of variables x_i (i=1:4) for which the degree of corresponding MF is equal to 1 ($\mu(x_i)$ = 1) (Source: Author)

Variable	Type of fuzzy set				
	Very low	Low	Medium	High	Very high
	Symmetric approach				
x_1	20	45	70	95	120
x_2	30	52.5	75	97.5	120
x_3	20	40	60	80	100
x_4	22	38.5	55	71.5	88
	The asymmetric approach based on the mean value				
x_1	20	34.73	49.46	84.73	120
x_2	30	49.22	68.44	94.22	120
x_3	20	41.26	62.52	81.26	100
x_4	22	44.29	66.58	77.29	88
	The asymmetric approach based on mean and extreme values				
x_1	[20,26]	37.73	49.46	62.73	[76,120]
x_2	[30,49]	58.72	68.44	77.22	[86,120]
x_3	[20,24]	43.26	62.52	72.76	[83,100]
x_4	[22,34]	50.29	66.58	77.29	88

The second approach is based on the asymmetric principle, taking the mean value from the sample as the point for which the central MF has the maximum degree (equal to 1). As can be seen from Table 36, the value 49.46 is the value of variable x_1 for which $\mu(x_1)$ = 1 for the MF *Medium* (MA).

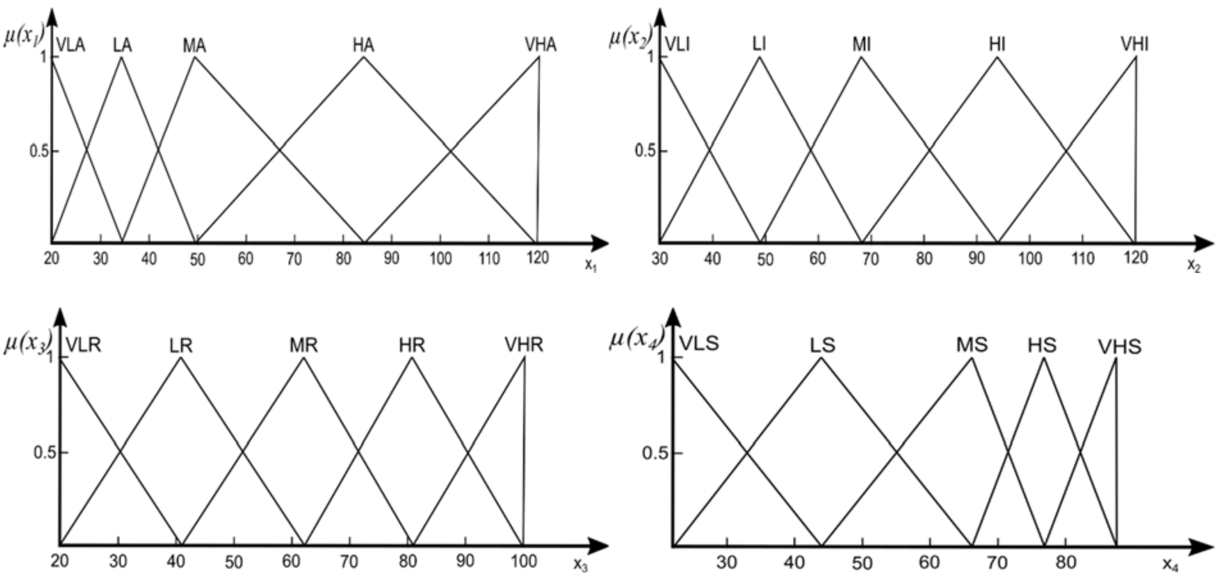


Fig. 26 MFs for input variables defined by the asymmetric principle based on the mean value (Source: Author)

The limit values of a variable x_1 are taken as $\mu(x_1)$ = 1 for the MF *Very low* (20) and *Very high* (120). The space between the mean and limit values is symmetrically divided, where the position of the axis of symmetry is a point where $\mu(x_1)$ = 1 for the fuzzy sets *Low* (34.73) and *High* (84.73). The same principle is implemented for the remaining three input variables and the input variables are designed by the second approach as shown in Figure 26.

The third approach is based on the asymmetric principle, where the characteristic points are the mean and extreme values from the data sample. For example, the possible values of the variable *aggressiveness* are from 20 to 120. Considering the values from the sample of 305 drivers, the minimum value was 26 and the maximum 76. Based on the proposed approach, the scores below 26 belong to the fuzzy set *very low aggressiveness* (VLA) with the value of MF equal to 1 ($\mu(x_1)$ = 1). On the other hand, scores above 76 are in the fuzzy set *very high aggressiveness* (VHA), also with the value of MF equal to 1. The value 49.46 was taken as the highest MF value ($\mu(x_1)$ = 1) in the fuzzy set *medium aggressiveness* (MA), the same as in the second method. The remaining two MFs, LA and HA were defined between the extreme values from the sample and mean, as shown in Figure 27. Other input variables are defined in the same manner.

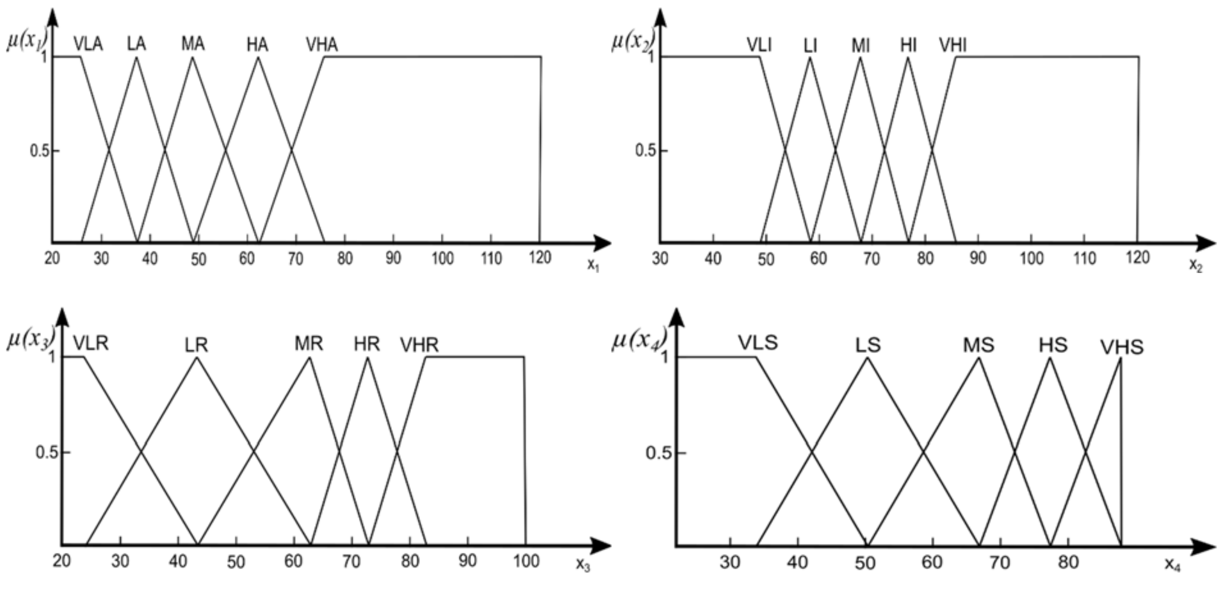


Fig. 27 MFs for input variables defined by the asymmetric principle based on mean and extreme values (Source: Author)

To describe the output variable, seven MFs were introduced unlike the cases for input variables where five MFs were used. The domain of output variable covers just 9 points; however, the number of MFs is increased in this case because the RTAs are relatively rare events and the intention was to describe each category of drivers as precise as possible. The following MF were introduced: *very small number of accidents* (VSNA), *small number of accidents* (SNA), *moderately small number of accidents* (MSNA), *medium number of accidents* (MNA), *moderately high number of accidents* (MHNA), *high number of accidents* (HNA), and *very high number of accidents* (VHNA). The variable y was defined as shown in Figure 28.

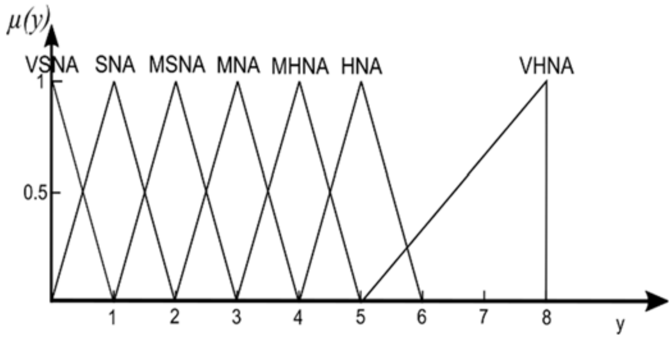


Fig. 28 MFs for the output variable (Source: Author)

Testing of the proposed approaches for defining variables in the FIS is done by the optimization procedure using the proposed BCO algorithm. Each input variable is described by five MFs. For MF *number 1* just the parameter of this MF that is of the highest value at x_i axis is tested, while for MF *number 5* just the parameter of the lowest value at x_i axis is considered. In the case of MFs *numbers 2*, *3,* and *4*, all three parameters of each triangular MF are tested. In total, there are 11 parameters analyzed for each variable. Since there are four input variables, each of them described by five MFs, the total number of parameters (P) to be examined is 44. As previously explained in Section 2, testing a parameter represents a forward pass, therefore NP=44. When testing a parameter, the domain of possible values should be determined. For this purpose, to provide the overlapping of corresponding MFs and to maintain the required order of considered parameters at x_i axis, there are 88 constraints set. These constraints will be explained in the following text, for the concrete case of variable x_1 where 22 constraints are defined. However, the principle of forming constraints is the same for other variables.

To implement the Eq. (7), it is necessary to set the constraints, i.e. the range where $P'_f(ch)$ can take the values. Accordingly, we need to define P_{fmin} and P_{fmax}. First, the notation used in the constraints should be noticed in Figure 29. As can be noticed, we use the symbol R for the parameter of MF that is the “right” bound of the MF which name is in the index of symbol R, and L for the parameter that is "left" bound of considered MF. The points at x-axis where MF has the maximum degree (μ(x)=1) is marked with M_{MF}, for example M_{VLA} for MF named VLA. In the considered case, the parameters:

R_{VLA_min} , L_{LA_min} , M_{LA_min} , R_{LA_min} , L_{MA_min} , M_{MA_min} , R_{MA_min} , L_{HA_min} , M_{HA_min} , R_{HA_min} , L_{VHA_min} denotes P_{fmin} , while

R_{VLA_max} , L_{LA_max} , M_{LA_max} , R_{LA_max} , L_{MA_max} , M_{MA_max} , R_{MA_max} , L_{HA_max} , M_{HA_max} , R_{HA_max} , L_{VHA_max} represents P_{fmax}.

Besides, another factor that appears in the constraints is ODC, representing an overlapping and distance constant. A case when ODC represents the minimum allowed overlapping is presented in part (c) of Figure 30, while the same value of ODC can be used as the minimum allowed distance between two membership functions for the points with the maximum degree (μ(x)=1) illustrated in part (d) of Figure 30. In the proposed algorithm, the value of ODC should be calculated for each variable, by the Eq. 20, where LB is the lower bound of the domain of the variable, RB is the upper bound of the domain of the variable, and n_{MF} is the number of MFs that describes the considered variable. The Eq. (20) is set according to the authors' opinion; however, the condition about overlapping can be set also in some other way. Some authors even do not set it in the procedure of MF tuning. For example, Nikolić, Šelmić, Macura, and Ćalić (2020) allow the cases with minimal overlapping of MFs, or even the cases where MFs do not even "touch" between themselves, leaving in this way some parts of the variable's domain uncovered by MFs (part (a) in Figure 30). In addition, their algorithm creates FIS structures with illogical membership functions (Part (b) of Figure 30). The authors of the paper Nikolić, et al. (2020) accept and perform testing of FIS structures where some parts of the variable's domain remain uncovered or the cases with illogical membership functions; however, in the further procedure of their algorithm, during the calculation of the objective function of the considered problem, a penalty is added to discourage the algorithm from keeping these solutions. To avoid this kind of procedure, in this dissertation, the ODC is introduced to prevent the unwanted FIS structures from the beginning of the algorithm, by that improving the performance of the algorithm execution.

$$ODC = \frac{RB - LB}{n_{MF}} * 10\% \quad (20)$$

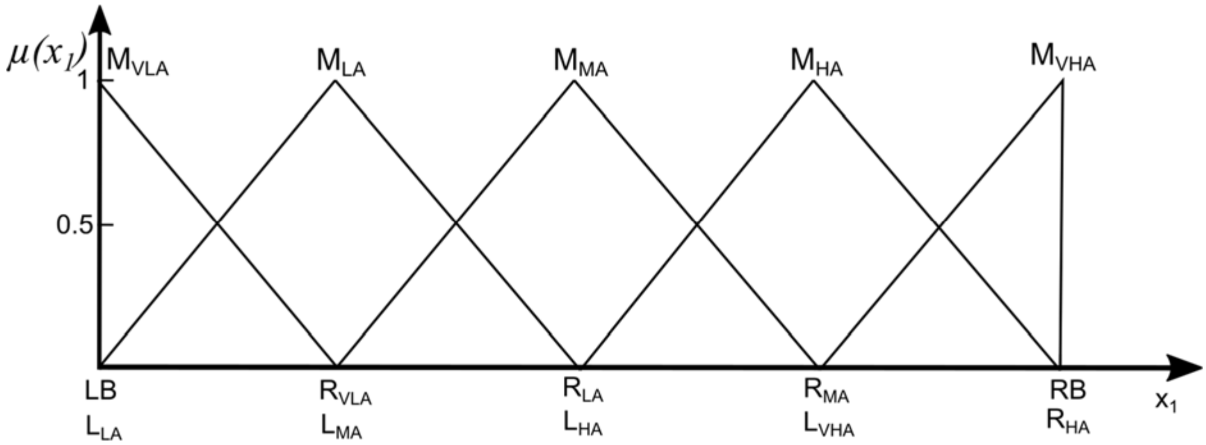


Fig. 29 The notation used in the constraints (Source: Author)

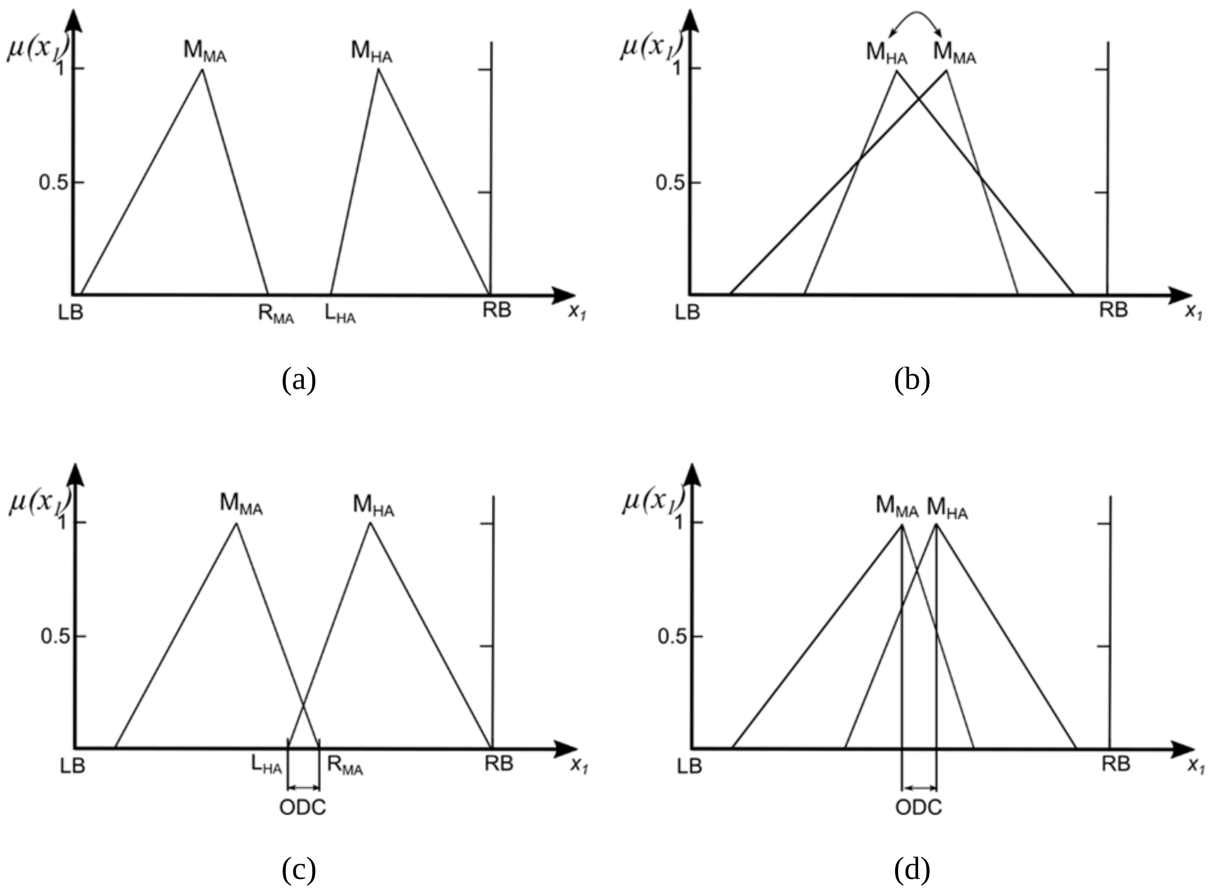


Fig. 30 Illustration of different constraints concerning $P_f(ch)$ domains: (a) uncovered domain of the variable – Figure adjusted from Nikolić et al. (2020); (b) illogical membership functions – Figure adjusted from Nikolić et al. (2020); (c) the minimum allowed overlapping in the proposed algorithm – ODC value; (d) the minimum allowed distance between two membership functions for the points with the maximum degree (μ(x)=1) in the proposed algorithm – ODC value (Source: Author)

After the explanation of used notation, the constraints in the case of the input variable x_1, with the aim to calculate R_{VLA} , L_{LA} , M_{LA} , R_{LA} , L_{MA} , M_{MA} , R_{MA} , L_{HA} , M_{HA} , R_{HA} , L_{VHA} are set in the following way:

For VLA:
$R_{VLA\_min} = M_{VLA} + ODC$;
$R_{VLA\_max} = (M_{LA} + M_{MA})/2$.

For LA:
$L_{LA\_min} = LB$;
$L_{LA\_max1} = R_{VLA} - ODC$; $L_{LA\_max2} = M_{LA} - ODC$;
$L_{LA\_max} = \min(L_{LA\_max1}, L_{LA\_max2})$.
$M_{LA\_min1} = LB + 2 * ODC$; $M_{LA\_min2} = L_{LA} + ODC$;
$M_{LA\_min} = \max(M_{LA\_min1}, M_{LA\_min1})$;
$M_{LA\_max1} = M_{MA} - 2 * ODC$; $M_{LA\_max2} = R_{LA} - ODC$;
$M_{LA\_max} = \min(M_{LA\_max1}, M_{LA\_max2})$.
$R_{LA\_min1} = M_{LA} + ODC$; $R_{LA\_min2} = L_{MA} + ODC$;
$R_{LA\_min} = \max(R_{LA\_min1}, R_{LA\_min2})$;
$R_{LA\_max} = (M_{MA} + M_{HA})/2$.

For MA:
$L_{MA\_min} = (M_{VLA} + M_{LA})/2$;
$L_{MA\_max1} = R_{LA} - ODC$; $L_{MA\_max2} = M_{MA} - ODC$;
$L_{MA\_max} = \min(L_{MA\_max1}, L_{MA\_max2})$.
$M_{MA\_min1} = M_{LA} + 2 * ODC$; $M_{MA\_min2} = L_{MA} + ODC$;
$M_{MA\_min} = \max(M_{MA\_min1}, M_{MA\_min2})$;
$M_{MA\_max1} = M_{HA} - 2 * ODC$; $M_{MA\_max2} = R_{MA} - ODC$;
$M_{MA\_max} = \min(M_{MA\_max1}, M_{MA\_max2})$.
$R_{MA\_min1} = M_{MA} + ODC$; $R_{MA\_min2} = L_{HA} + ODC$;
$R_{MA\_min} = \max(R_{MA\_min1}, R_{MA\_min2})$;
$R_{MA\_max} = (M_{HA} + RB)/2$.

For HA:
$L_{HA\_min} = (M_{LA} + M_{MA})/2$;
$L_{HA\_max1} = R_{MA} - ODC$; $L_{HA\_max2} = M_{HA} - ODC$;
$L_{HA\_max} = \min(L_{HA\_max1}, L_{HA\_max2})$.
$M_{HA\_min1} = M_{MA} + 2 * ODC$; $M_{HA\_min2} = L_{HA} + ODC$;
$M_{HA\_min} = \max(M_{HA\_min1}, M_{HA\_min2})$;
$M_{HA\_max1} = RB - 2 * ODC$; $M_{HA\_max2} = R_{HA} - ODC$;
$M_{HA\_max} = \min(M_{HA\_max1}, M_{HA\_max2})$.

$$R_{HA\_min1} = M_{HA} + ODC;\ R_{HA\_min2} = L_{VHA} + ODC;$$
$$R_{HA\_min} = \max(R_{HA\_min1}, R_{HA\_min2});$$
$$R_{HA\_max} = RB.$$

For VHA:
$$L_{VHA\_min} = (M_{MA} + M_{HA})/2;$$
$$L_{VHA\_max1} = R_{HA} - ODC;\ L_{VHA\_max2} = RB - ODC;$$
$$L_{VHA\_max} = \min(L_{VHA\_max1}, L_{VHA\_max2}).$$

It should be noticed that the concrete values in the set conditions, considering this explained variable and also others in the FIS structure, are dynamically changing during the execution of the algorithm. It means that each formed FIS in the testing procedure has its conditions that characterize the concrete fuzzy system.

Other parameters of the implemented BCO algorithm are the following: B=4, NC=5, IT=20. The number of 20 iterations is chosen based on the author's assumption that a certain trend can be noticed by comparing 20 results. The simulation procedure implied 10 experiments for each considered approach for defining variables. The number of 10 experiments is chosen based on the author's assumption that an appropriate conclusion can be reached about the regularity in obtained results by repeating 10 experiments. For each iteration, the mean values of 10 experiments are presented in Figure 31.

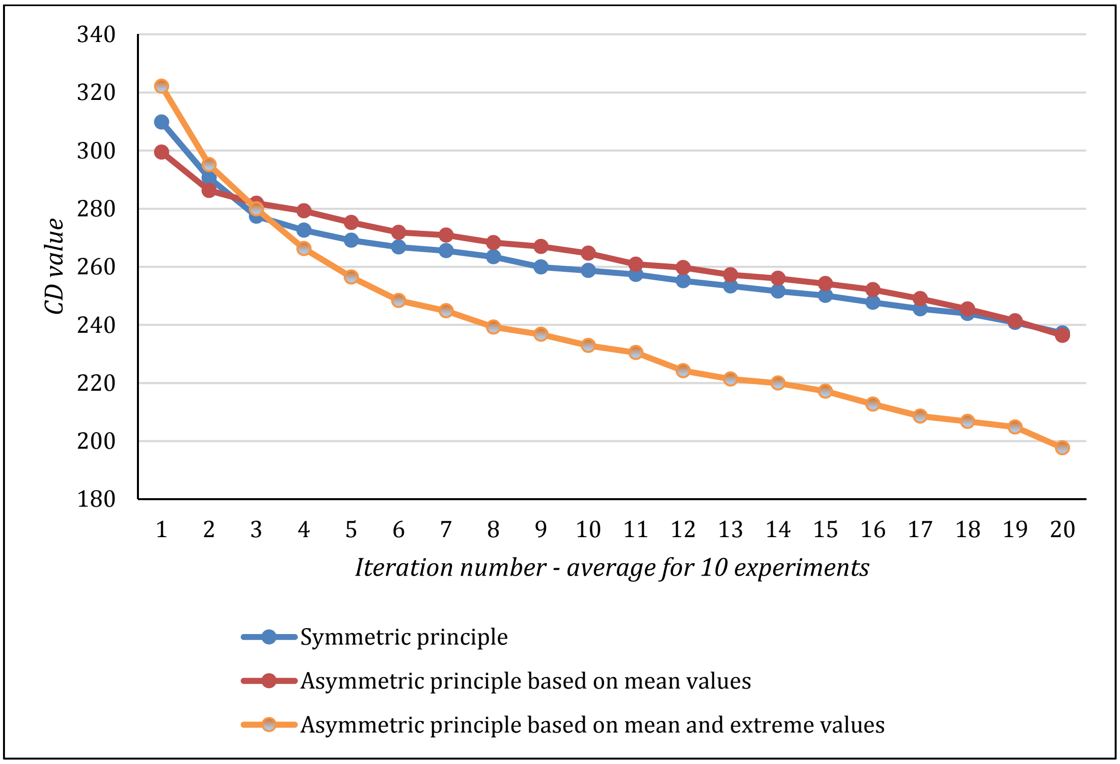


Fig. 31 A comparison between three approaches for defining variables of FIS based on average CD values in 10 experiments with 20 iterations (Source: Author)

Having in mind that there are 4 bees, 5 changes made by each bee in a forward pass, 44 forward passes, 20 iterations, 10 experiments, 3 approaches and that each FIS is tested on the sample of 305 drivers, the results present in Figure 31 are based on 161,040,000 evaluated fuzzy inference systems. The total execution time is around 90 hours, i.e. almost 4 days.

Figure 31 gives also the answer to one of the aims of this research, which was to examine the effects of initial FIS structures in the optimization procedure. There are three proposed approaches: the Symmetric approach, the Asymmetric approach based on the mean value, and the Asymmetric approach based on mean and extreme values. The proposed BCO algorithm confirmed that the third method gives the best results. This conclusion may be useful twofold. First, having in mind that the third method for defining variables is the most suitable, the initial FIS in the optimization procedure can be easier and more effectively defined. Second, in the case when there is a task just to form a FIS for some purpose and there is a lack of time for the optimization procedure, by using the third method, the designed FIS will more probably offer better solutions than created randomly or by using other two tested methods.

Tab. 37 The minimal values of CD in 10 experiments for each considered approach (Source: Author)

Experiment Number	Symmetric approach (CD)	The asymmetric approach based on the mean value (CD)	The asymmetric approach based on mean and extreme values (CD)
1	243.9240	247.5702	207.5843
2	241.1064	245.7423	203.4848
3	240.9741	242.2948	202.8990
4	239.1694	241.0987	202.0099
5	238.6924	240.2350	198.9663
6	237.9139	233.1188	194.0601
7	237.0992	232.9170	193.4670
8	234.9182	230.5881	192.3154
9	230.4864	227.3439	191.4037
10	227.4326	222.9927	190.6803

Finally, the task is to find a FIS with a minimum value of the objective function. This would be the best found FIS that can be used as a decision-making tool for various purposes in the transportation field. The results of the best found FIS structures after each experiment are presented in Table 37. The results of all 600 simulations for each of the three approaches are shown in Appendix B.

5.5.3 The best-found FIS

The best-found FIS is created by the asymmetric approach based on mean and extreme values and its CD value is equal to 190.6803. To illustrate the level of improvement achieved by the implementation of the proposed BCO based algorithm, the relationship between FIS structures that are not optimized by the proposed algorithm and also multiple regression analysis, and the best-found FIS are shown in Figure 32.

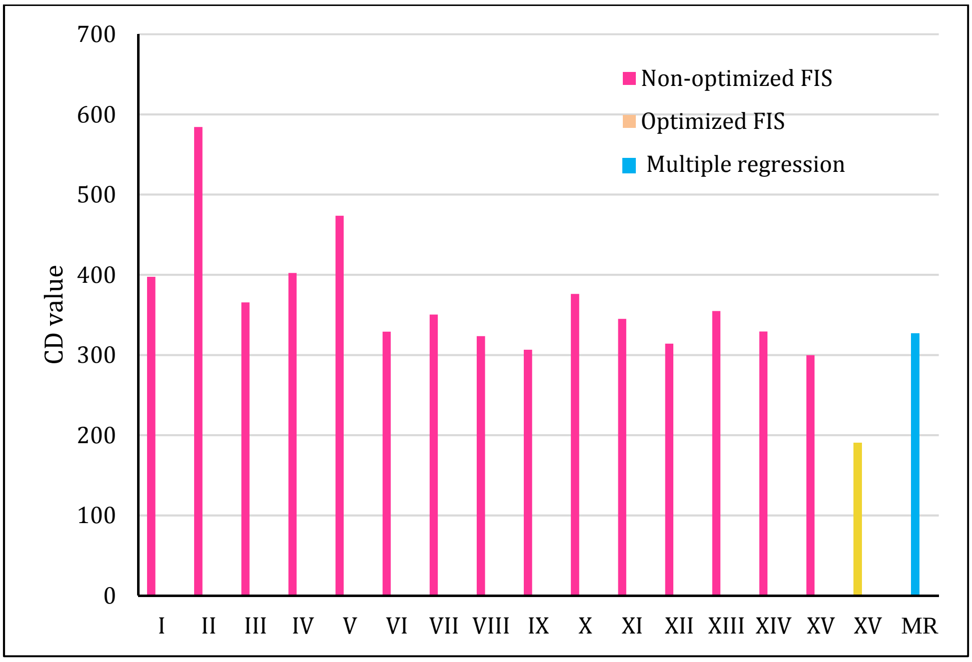


Fig. 32 A relationship between the optimized FIS, non-optimized FIS structures, and multiple regression analysis (Source: Author)

The individual results of this FIS compared to the empirical results concerning the number of RTAs in the sample are shown in Figure 33. This Figure indicates that the considered FIS provides solutions that mitigate the extreme values about the number of RTAs, i.e. when it comes to respondents who did not experience accidents, the solutions of FIS are not always equal to zero, but close to zero. On the other hand, when it comes to respondents who experienced a larger number of accidents, the FIS gives values that are slightly less than that value.

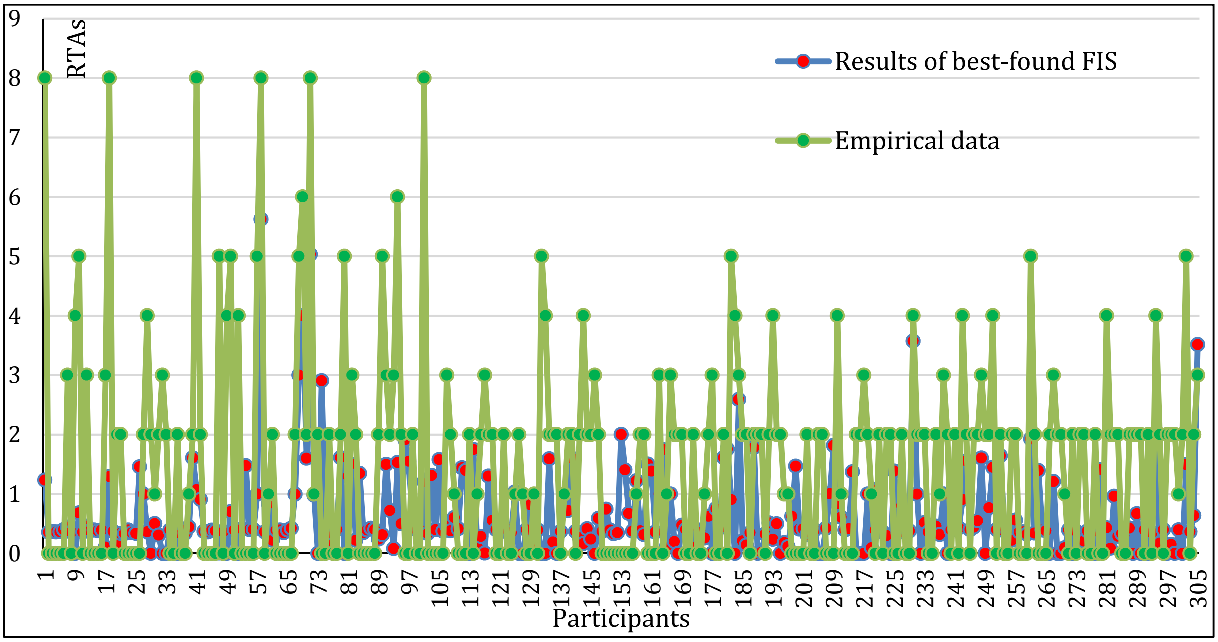


Fig. 33 A relationship between the empirical data and results of the best-found optimized FIS (Source: Author)

To further illustrate the characteristics of the best-found FIS, the position of MFs and fuzzy rules should be considered. The MFs of input variables of the best-found FIS are presented in Figure 34. On the other hand, as previously explained, fuzzy rules in the proposed BCO algorithm are designed based on the Wang-Mendel approach. This approach implies the principle of „one data pair – one rule“, however, considering the sample of 305 participants, there are 121 fuzzy rules generated from these data. The remaining 184 rules are eighter the same or conflict to these 121 rules. The list of fuzzy rules obtained by the Wang-Mendel approach is presented in Appendix C.

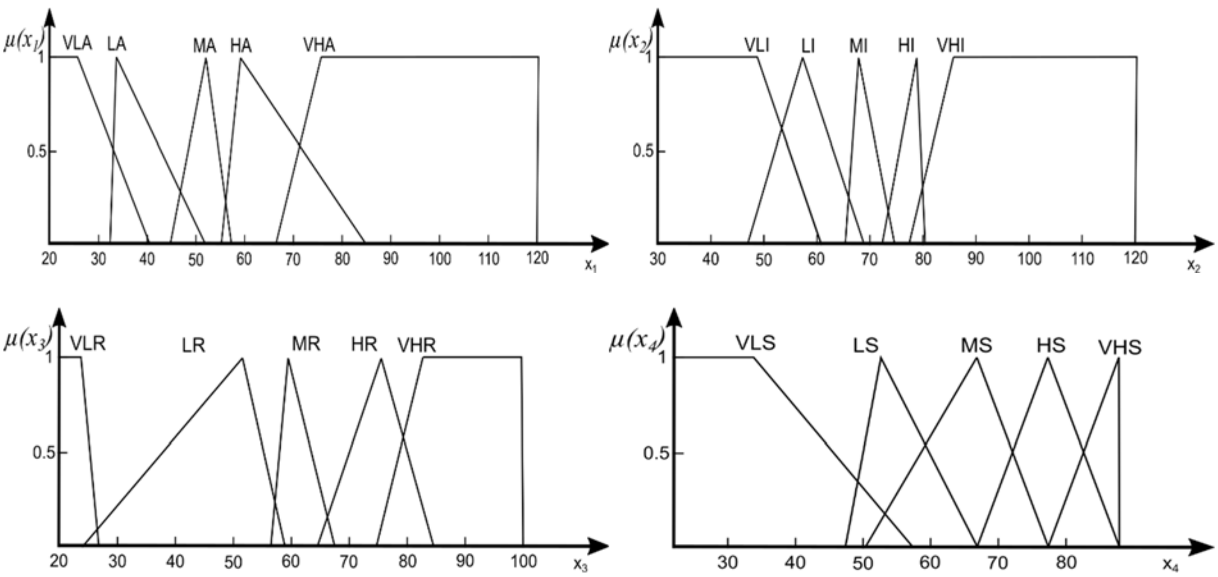


Fig. 34 MFs for input variables of the best found FIS (Source: Author)

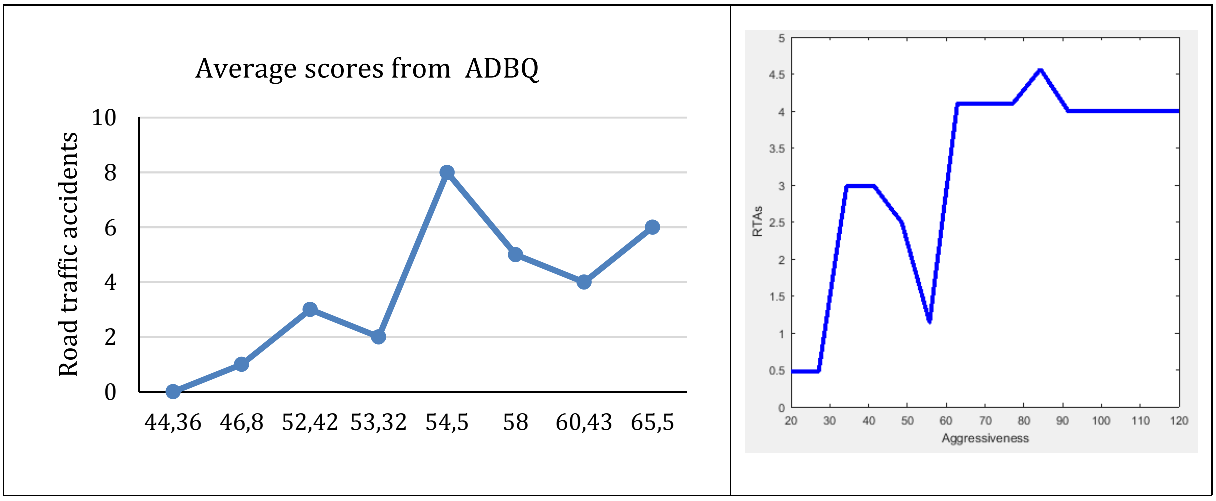
Further, from Figure 35 to 38, there are 2D maps of relationships between a concrete input variable and the number of RTAs. By analyzing these maps, it can be concluded that the modeling process of driver behavior in the best-found FIS is not based on linearity, but more concrete to the empirical data. This case is one more confirmation that by fuzzy logic, complex systems that are not totally linear can be successfully modeled.

Besides, it is interesting to observe the average values that the respondents achieve in a certain category, i.e. respondents with a certain number of accidents, and to compare the observed trend with the corresponding variable that appears within the best-found FIS. In Table 38, the average values of scores achieved by the respondents from four used psychological instruments are presented, observed by categories per the number of accidents experienced by the participants.

Tab. 38 Average values of scores observed in categories per the number of RTAs (Source: Author)

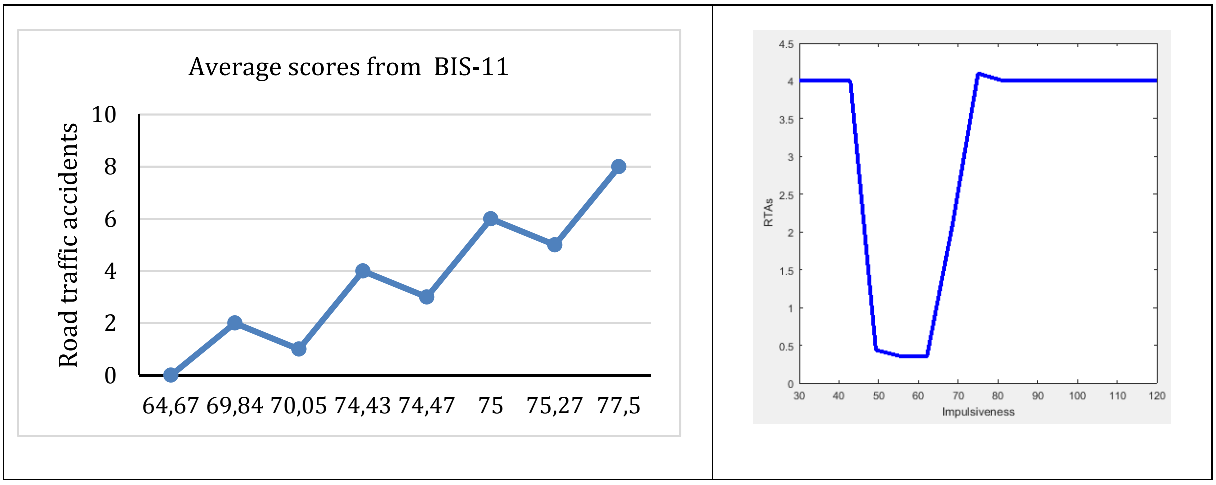
Number of RTAs	Average scores from ADBQ	Average scores from BIS-11	Average scores from Manchester DAQ	Average scores from Self-assessment questionnaire
0	44,36	64,67	59,14	67,50
1	46,80	70,05	65,10	71,10
2	53,32	69,84	64,98	69,64
3	52,42	74,47	61,32	61,68
4	60,43	74,43	68,21	56,00
5	58,00	75,27	67,91	52,00
6	65,50	75,00	71,50	50,00
8	54,50	77,50	67,67	53,33

Therefore, in Figures 35 to 38, there are comparative graphs of particular input variables. Part a) of these figures is made from average scores obtained from the considered 305 participants, observed per category of drivers considering the number of RTAs. On the other hand, part b) of the mentioned figures represents a relationship between the considered input variable and the number of RTAs in the best-found FIS. Part b) in these figures is obtained by using the MATLAB application "Surface Viewer".



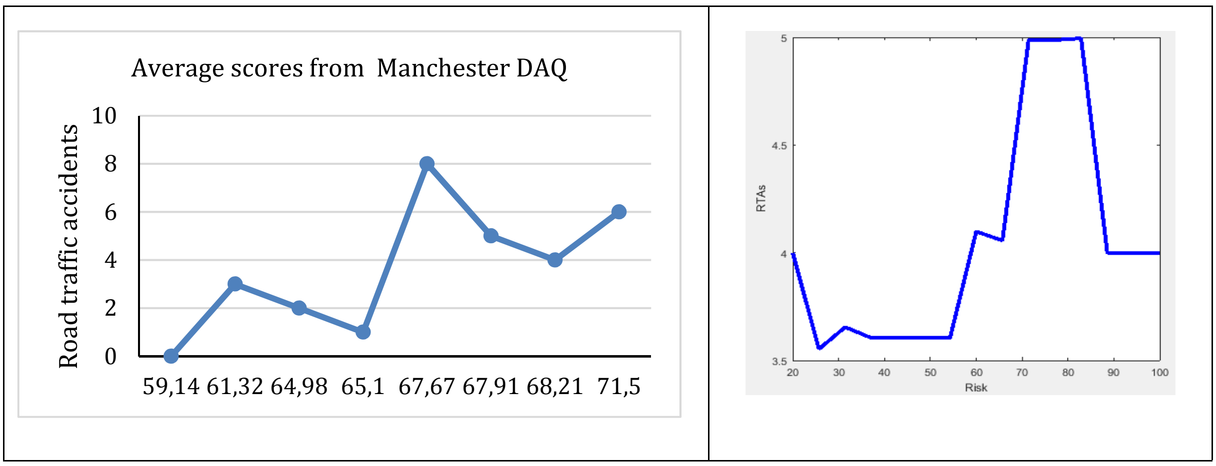
a) b)

Fig. 35 A relationship between the variable Aggressiveness in the empirical research (a) and in the best-found FIS (b) (Source: Author)



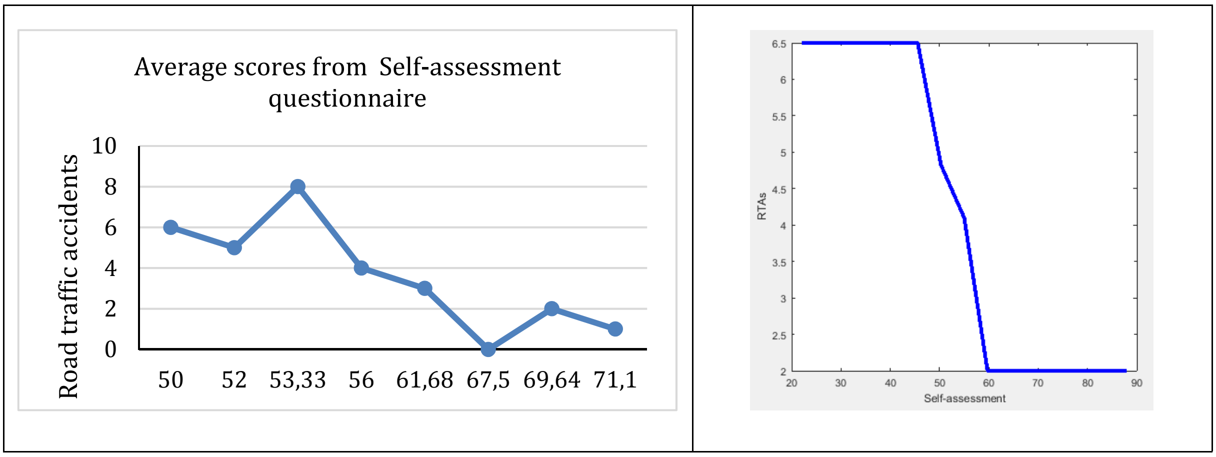
a) b)

Fig. 36 A relationship between the variable Impulsiveness in the empirical research (a) and in the best-found FIS (b) (Source: Author)



a) b)

Fig. 37 A relationship between the variable Risk in the empirical research (a) and in the best-found FIS (b) (Source: Author)



a) b)

Fig. 38 A relationship between the variable Self-assessment in the empirical research (a) and in the best-found FIS (b) (Source: Author)

Based on the analysis of the average values of scores achieved on psychological instruments in each of the categories in terms of the number of experienced RTAs, the trends can be noticed, i.e. relationships between individual variables and the number of accidents. Even though the average scores make a relatively linear trend, by analyzing the concrete results of each participant, the best-found FIS models driver behavior in a non-linear way.

6 Conclusions

By reviewing the literature, it is concluded that the topic of explaining driver behavior is very important and contemporary because its better understanding can contribute to saving many lives on the roads. Further, to design a model for explaining driver behavior, it is concluded to be useful to consider two types of psychological traits of drivers – innate and acquired. Speaking about the innate, the studies confirm that the most significant psychological traits of drivers who are characterized by risky behavior in traffic and who are prone to participate in RTAs are aggressiveness and impulsiveness. Accordingly, two psychological instruments that measure these traits are chosen. When it comes to the acquired traits, which are considered as more convenient for the subsequent corrective measures of the risky drivers, they relate to the attitudes and self-assessment. Two additional psychological instruments that measure these constructs in traffic are introduced.

After a collection of data about the scores from four considered psychological instruments examining 305 participants, the adequate research methods were used to reach the appropriate conclusions. For this type of research, convenient statistic methods are the hierarchical regression analysis and binary logistic regression. A further method that brings to improved modeling of driver behavior relates to the use of fuzzy logic. However, the proposed fuzzy inference system is additionally improved by implementing the original BCO based algorithm proposed in this dissertation.

Based on the achieved results, it can be stated that the set goals of this dissertation are achieved. By reviewing the literature from the field of explaining driver behavior, it can be concluded that the proposed methodology of research in this dissertation is new and original. There is no evidence of using four considered instruments together (Aggressive Driving Behavior Questionnaire - ADBQ, the Barratt Impulsiveness Scale - BIS-11, the Manchester Driver Attitude Questionnaire - DAQ, and the Questionnaire for Self-Assessment of Driving Ability) for explaining driver behavior.

Further, the use of the same instruments was combined with the fuzzy logic to form a model for assessing driver propensity for RTAs. The fuzzy logic is particularly convenient to be used in this kind of model because a measurement or assessment of psychological traits always contains a certain level of fuzziness and approximations even in the cases where the scores from psychological instruments are exactly expressed with crisp values. Based on the obtained results, fuzzy logic was shown to be a more convenient technique for modeling driver behavior, offering better results when compared to multiple regression analysis. The proposed FIS is further improved by the original algorithm proposed in this dissertation. This algorithm is based on the BCO metaheuristic.

The outcome of this study is a proposal for the methodology consisting of the implementation of the hierarchical regression analysis, binary logistic regression, multiple regression analysis, fuzzy inference systems, and bee colony optimization metaheuristic, which purpose is to model driver behavior. The original models for assessing the circumstances of traffic accidents occurrence based on the driver's personality traits related to the impulsiveness, aggressiveness, attitudes, and self-assessment of personal driving abilities are proposed and tested on the real data collected for the purpose of this dissertation. As a final result, there is a decision-making model designed to assess a driver propensity for traffic accidents. The main decision-making model is based on the implementation of the FIS and BCO metaheuristic where input variables relate to the considered psychological traits of driver and output variable to the number of experienced RTAs.

The recommendation for future research can be to broaden the optimization algorithm to the different shapes of MFs or to another number of MFs. Additionally, since the fuzzy rules base is formed in this paper based on the Wang-Mendel method, testing some other approach would be welcome. A meaningful direction for future research would certainly be to test other optimization algorithms that could be used for the process of FIS structure optimization.

When it comes to the limitations of this research, it should be kept in mind that the results are based on the data collected by the drivers' self-reports. Such methods of data collection can lead to distortions due to socially desirable answers. Although respondents were familiar with the anonymous nature of testing as well as guaranteed confidentiality of the collected data, it is assumed that they still had some kind of restraint in responding concerning certain aspects of behavior. This is particularly evident in the case of professional drivers since it is known as a rule that this population gives socially desirable answers. Further research directions should be focused towards minimization or elimination of these limitations.

However, despite the mentioned limitations, the results of this study indicate an important role of certain personality traits in risky behavior in traffic. These findings could find their practical applicability for different purposes.

Because the proposed FIS provides information about driver propensity for RTAs, the criteria used in the selection of professional drivers could be significantly improved. Certainly, the transportation companies have an interest to hire drivers who are not prone to participate in RTAs; however, this is also the interest of society as a whole. The recruitment procedure would involve the use of proposed instruments for assessing personality traits along with the psychomotor tests. When it comes to the implementation of the decision-making tool proposed in this Ph.D. dissertation, the procedure would be very simple. A human resource professional would collect the data concerning the candidate's personality traits using four determined instruments. The obtained scores should be inserted as inputs in the best-found FIS, and the result about the propensity for RTAs would be automatically calculated by using appropriate software.

In addition, the proposed decision-making tool for explaining driver behavior may have its practical implication in the design of training and education processes for candidates applying for a driving license. Furthermore, programs for the prevention of accidents and violations of laws, or for the rehabilitation of drivers who have been deprived of their driving license may be developed more effectively, according to the personality traits of the driver. Further, the results of this research could be usefully applied for some categories of vulnerable drivers to raise awareness about the consequences of risky behavior in traffic. For example, young drivers show a high rate of involvement in RTAs, especially at the beginning of their driving experience.

Finally, the main contributions of this dissertation can be structured in several fields. The first relates to a comprehensive review of the literature related to the RTAs, driver behavior, and implemented research methods. Further, the original research methodology and original decision-making tool for explaining the driver behavior is proposed. To test the proposed methodology, a survey is carried out involving 305 participants. The proposed methodology proved to be useful for explaining driver behavior and the results of this dissertation have both scientific and practical implications. From the scientific point of view, the original methods and algorithms are proposed, making a significant contribution, especially in the field of optimization algorithms. Speaking about the practical implications, the proposed decision-making tool can be used in practice, offering various benefits, from saving the lives of people in traffic to significant economic and social benefits.

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List of Appendices

Appendix A – Implemented questionnaires

Appendix A1 – Demographic and driving history questionnaire

Demographic and driving history questionnaire

Dear participants,

This survey is part of the research related to the behavior of drivers, which is conducted within the doctoral dissertation. To get as credible information as possible, it is very important that your answers are honest. It is certainly important to point out that this survey is ANONYMOUS, and that the obtained results will be used exclusively for scientific purposes.

Please circle one of the offered answers:

[1] Gender:

a) Female b) Male

[2] Category of the driver:

a) the driver of privately owned vehicle
b) bus drivers
c) truck drivers

[3] Age:

a) under 30 years old b) between 31 and 45

c) between 46 and 60 d) above 60 years old

[4] How many kilometres you are driving within a year?

a) under 50,000 km b) between 50,000 and 100,000

c) between 100,000 and 200,000 d) above 200,000 km

[5] What type of vehicle do you drive most often?

a) transit bus (city bus for public transport)
b) coach bus (tourist travels)
c) intercity bus (public transport between cities)
d) truck (rigid vehicle)
e) truck with trailer
f) car

[6] How long do you have a driving license?

a) under 5 years
b) between 6 and 15 years
c) between 16 and 25 years
d) between 26 and 35 years
e) above 36 years

[7] How often do you drive outside the city (your settlement)?

a) every day
b) 3 to 5 times a week
c) twice a week
d) once a week
e) 2 to 3 times a month
f) once a month or less often

[8] In your opinion, what is the main cause of road traffic accidents?

a) human factor
b) vehicle
c) road characteristics
d) environmental issues
e) something else

[9] What is your maximum driving speed when you are on a two-lane rural highway? (main local roads passing through the settlements where the speed limit is 50 km/h and between settlements where the speed limit is from 70 to 90 km/h)

a) 50 km/h
b) 70 km/h
c) 90 km/h
d) 100 km/h
e) 120 km/h or more

[10] In your opinion, what is the maximum driving speed of other vehicles on a two-lane rural highway?

a) 50 km/h
b) 70 km/h
c) 90 km/h
d) 100 km/h
e) 120 km/h or more

[11] How many road traffic accidents with your fault have you experienced? (professionally and privately)

a) 0
b) 1
c) 2
d) 3
e) 4
f) 5
g) 6
h) 7
i) 8

Appendix A2 –Aggressive Driving Behaviour Questionnaire

Aggressive Driving Behaviour Questionnaire

Directions: Circle the response (1 through 6) that most accurately describes how often you perform the behaviors specified in the items below.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[1] You become agitated or enraged when other drivers impede you, aren't paying attention, or drive poorly around you on the road.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[2] You travel above the speed limit, even if you have more than enough time to reach your destination.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[3] When other drivers do get on your nerves, how often do you think negatively of them without reacting verbally?

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[4] You think that other drivers just aren't thinking or paying enough attention when they anger you with their driving.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[5] When other drivers annoy or anger you, you try to think positively or just accept there are frustrating situations while driving.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[6] In cases where you know you can get away with it, you have no problem breaking minor laws or rules.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[7] When another driver angers you while on the road, you follow very close (tailgate) or otherwise try to scare them.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[8] You give the finger to drivers who annoy or anger you.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[9] When another driver angers you while on the road, you shout verbal insults towards then, even if they cannot hear you.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[10] You stick your tongue out or make faces at drivers that annoy you or make you mad.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[11] You drive intoxicated even when you realize that you may be over the legal limit.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[12] When another driver angers you at night, you shine your brights in their rearview mirror.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[13] You find being stuck in traffic or behind a slow driver especially annoying.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[14] When another driver anger you while on the road, you attempt to get revenge on them.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[15] You find drivers that are impatient (ex. Weave in and out of traffic, disregard stop signs, etc.) especially annoying.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[16] While driving, you fail to notice signs or other cars, misjudge other‟s speed, etc.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[17] You „wake up‟ to realize that you have no clear recollection of the road along which you have just traveled.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[18] You take chances and run through red lights.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[19] If another driver is following too closely, you slow down or hit your breaks to get them to back off.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

[20] You shake your head at a driver who annoys you.

Never	Hardly at all	Occasionally	Often	Quite frequently	Nearly all the time
1	2	3	4	5	6

Appendix A3 –Barratt Impulsiveness Scale

Barratt Impulsiveness Scale (BIS-11) Questionnaire

DIRECTIONS:

People differ in the ways they act and think in different situations. This is a test to measure some of the ways in which you act and think. Read each statement and put an X on the appropriate circle on the right side of this page. Do not spend too much time on any statement. Answer quickly and honestly.

Rarely/Never	Occasionally	Often	Almost Always/Always
1	2	3	4

[1]	I plan tasks carefully.	1	2	3	4
[2]	I do things without thinking.	1	2	3	4
[3]	I make-up my mind quickly.	1	2	3	4
[4]	I am happy-go-lucky.	1	2	3	4
[5]	I don’t “pay attention.”	1	2	3	4
[6]	I have “racing” thoughts.	1	2	3	4
[7]	I plan trips well ahead of time.	1	2	3	4
[8]	I am self controlled.	1	2	3	4
[9]	I concentrate easily.	1	2	3	4
[10]	I save regularly.	1	2	3	4
[11]	I “squirm” at plays or lectures.	1	2	3	4
[12]	I am a careful thinker.	1	2	3	4
[13]	I plan for job security.	1	2	3	4

[14]	I say things without thinking.	1	2	3	4
[15]	I like to think about complex problems.	1	2	3	4
[16]	I change jobs.	1	2	3	4
[17]	I act “on impulse.”	1	2	3	4
[18]	I get easily bored when solving thought problems.	1	2	3	4
[19]	I act on the spur of the moment.	1	2	3	4
[20]	I am a steady thinker.	1	2	3	4
[21]	I change residences.	1	2	3	4
[22]	I buy things on impulse.	1	2	3	4
[23]	I can only think about one thing at a time.	1	2	3	4
[24]	I change hobbies.	1	2	3	4
[25]	I spend or charge more than I earn.	1	2	3	4
[26]	I often have extraneous thoughts when thinking.	1	2	3	4
[27]	I am more interested in the present than the future.	1	2	3	4
[28]	I am restless at the theater or lectures.	1	2	3	4
[29]	I like puzzles.	1	2	3	4
[30]	I am future oriented.	1	2	3	4

Appendix A4 – Manchester Driver Attitude Questionnaire

Manchester Driving Attitude Questionnaire (DAQ)

Instructions

To what extent do you agree or disagree with each of the following statements? Please read each statement carefully, and then circle the number that corresponds to your reply.

Strongly Disagree	Disagree	Neither agree or disagree	Agree	Strongly agree
1	2	3	4	5

[1]	Some people can drive perfectly safely after drinking three or four pints of beer	1	2	3	4	5
[2]	People stopped by the police for close following are unlucky because lots of people do it	1	2	3	4	5
[3]	I would welcome further use of double white lines to let me know when it is unsafe to overtake	1	2	3	4	5
[4]	Speed limits are often set too low, with the result that many drivers ignore them	1	2	3	4	5
[5]	I think the police should start breathalysing a lot more drivers around pub closing times	1	2	3	4	5
[6]	It is quite acceptable to take a slight risk when overtaking	1	2	3	4	5

[7]	Close following isn't really a serious problem at the moment	1	2	3	4	5
[8]	I know exactly how fast I can drive and still drive safely	1	2	3	4	5
[9]	Some drivers can be perfectly safe overtaking in situations which would be risky for others	1	2	3	4	5
[10]	Even one drink makes you drive less safely	1	2	3	4	5
[11]	I would favour stricter enforcement of the speed limit on 50 km per hour roads	1	2	3	4	5
[12]	Some people can drive perfectly safely even when they only leave a small gap behind the vehicle in front	1	2	3	4	5
[13]	The aim of the police should be to stop as many people as possible overtaking in risky circumstances	1	2	3	4	5
[14]	Even driving slightly faster than the speed limit makes you less safe as a driver	1	2	3	4	5
[15]	It's hard to have a good time if everyone else is drinking but you have to limit yourself because you're driving	1	2	3	4	5
[16]	I would be happier if close following regulations were more strictly applied	1	2	3	4	5
[17]	Stricter enforcement of speed limits on 50kmph roads would be effective in reducing the occurrence of road accidents	1	2	3	4	5
[18]	Even driving slightly too close to the car in front makes you less safe as a driver	1	2	3	4	5

[19]	I think it is O.K. to overtake in risky circumstances as long as you drive within your own capabilities	1	2	3	4	5
[20]	The law should be changed so that drivers aren't allowed to drink any alcohol	1	2	3	4	5

Appendix A5 – Questionnaire for Self-Assessment of Driving Ability

The Questionnaire for Self-assessment of Driving Ability

Instructions

To what extent do you agree or disagree with each of the following statements? Please read each statement carefully, and then circle the number that corresponds to your reply.

Strongly Disagree	Disagree	Agree	Strongly agree
1	2	4	5

	Dimension 1 *General driving ability*				
[1]	I am a champion on slippery conditions	1	2	3	4
[2]	I am well skilled to drive fast if necessary	1	2	3	4
[3]	I drive effectively under high traffic density conditions	1	2	3	4
[4]	I am well skilled to anticipate	1	2	3	4
[5]	I always judge gaps in traffic flow correctly	1	2	3	4
[6]	I have excellent driving skills	1	2	3	4
[7]	I am well skilled in dark driving	1	2	3	4
[8]	I know exactly how to turn the wheel when skidding	1	2	3	4
	Dimension 2 *Safety orientation*				
[9]	Dangerous situations rarely occur abruptly for me	1	2	3	4
[10]	I have a driving style avoiding dangerous situations	1	2	3	4
[11]	I am pretty good at driving safely	1	2	3	4

[12]	I recognize dangerous situations	1	2	3	4
[13]	I feel confident to cope with unexpected situations	1	2	3	4
[14]	I have lower accident risk than the average driver	1	2	3	4
	Dimension 3 *The body dimension*				
[15]	I have the feeling of direct contact with the road surface	1	2	3	4
[16]	The car and I are united	1	2	3	4
[17]	I know immediately if my car fits into a narrow passage	1	2	3	4
[18]	I know exactly the position of the car	1	2	3	4
[19]	I know the exact stopping distance needed for maximum braking	1	2	3	4
	Dimension 4 *Specific task skills*				
[20]	I am able to reverse fast and precisely into a garage	1	2	3	4
[21]	I am able to reverse easily by using rear-view mirrors	1	2	3	4
[22]	I am well skilled in fast and precise parallel parking	1	2	3	4

Appendix B – The results of simulations based on the implementation of the proposed BCO based algorithm

Appendix B1 – The results of 200 simulations in the symmetric approach

Iteration	Experiment No.									
No.	1	2	3	4	5	6	7	8	9	10
1	314.8767	340.8860	295.0344	271.7756	307.5900	333.4148	307.9979	309.1434	294.8141	322.0391
2	307.0217	327.3643	283.9018	267.5063	295.5581	274.5443	274.7731	299.9668	275.5087	299.8867
3	275.7031	273.3866	277.5488	262.7568	274.5407	270.9751	268.5682	298.7848	274.6401	296.7067
4	272.7614	261.4699	276.8988	262.5287	271.3528	270.4880	262.6033	295.5581	272.3619	279.5083
5	268.6145	261.3588	275.5476	261.6345	269.3214	269.3934	260.4962	278.4522	266.6459	279.4644
6	265.4691	260.8400	272.7490	259.2949	263.9765	265.5467	260.1730	278.4000	262.2223	279.2491
7	264.2731	259.1913	271.9670	258.8355	263.6161	265.1067	258.9032	276.7227	259.5376	276.9355
8	263.9911	256.1505	268.0175	256.6434	261.1326	262.5721	258.4536	275.7405	257.0145	274.4185
9	256.9535	255.3880	261.6138	254.6558	258.0194	260.4896	251.4123	274.0085	256.2877	270.2361
10	255.9459	255.3398	259.8780	253.4433	256.9206	258.5202	249.4167	273.1214	255.8274	268.4754
11	255.3366	254.0083	258.9094	252.9091	255.8922	258.0228	248.3445	270.2271	255.3032	264.4031
12	253.5061	250.3219	258.3150	250.9769	252.3771	255.0702	246.7289	267.0548	254.5667	262.6611
13	253.4360	250.1598	254.9778	248.9412	252.3438	255.0009	244.9253	260.3921	252.2949	261.3022
14	253.3979	249.6363	254.1278	247.3478	248.7356	254.9356	244.2431	256.0341	246.4819	260.9737
15	248.4059	248.5428	253.7589	246.6200	247.6994	254.8487	243.3029	254.9913	245.7960	257.1344
16	247.3687	247.6029	253.0387	243.7673	242.4896	250.9347	241.2202	254.4317	244.4025	252.2123
17	246.8423	246.8211	249.7930	240.8234	242.3100	250.8070	237.2003	245.3280	243.8065	251.4613
18	244.0114	243.9617	248.5670	239.9131	240.8692	248.6180	237.0992	244.3115	243.6015	248.1152
19	242.9527	242.2519	243.9964	239.1132	239.3566	246.2060	234.5065	241.7346	242.7246	235.4548
20	240.9741	234.9182	241.1064	237.9139	238.6924	243.9240	227.4326	239.1694	237.0992	230.4864

Appendix B2 – The results of 200 simulations in the asymmetric approach based on the mean value

Appendix B2 – The results of 200 simulations in the asymmetric approach based on the mean value

Iteration No.	Experiment No. 1	2	3	4	5	6	7	8	9	10
1	278.2452	286.4164	285.9333	294.7083	306.9952	308.8293	325.8940	279.4192	312.5109	315.2896
2	277.1556	286.0484	278.6026	280.6201	279.2792	292.5377	310.3652	274.4482	296.6248	286.7760
3	271.4257	279.2718	272.7448	279.4304	273.4442	291.1054	303.7608	267.6092	292.6993	286.7586
4	267.6394	276.9182	272.2388	277.4189	268.7923	290.3287	303.4804	266.9372	289.5875	278.7739
5	266.4896	272.9687	268.5303	274.0187	267.3953	287.4023	297.6693	266.7508	272.7861	278.2470
6	264.6843	270.4695	266.6909	271.3873	266.3970	274.9011	292.3216	266.2110	270.4415	274.5533
7	263.9624	268.5210	266.3567	269.8429	265.9342	274.3858	290.8077	266.1856	268.8923	274.0056
8	263.7725	265.4989	264.7915	269.4643	265.3058	273.1790	276.9698	264.6097	268.3493	270.9639
9	263.4352	264.7526	263.1051	268.2598	263.2153	269.4530	276.8753	263.3811	266.4246	270.8363
10	261.9821	262.1850	262.9684	266.1362	259.6655	266.0248	271.4581	263.3590	263.8456	268.8042
11	260.4818	260.0557	258.2952	264.9898	254.0965	261.1862	263.5395	260.9801	261.8417	263.1815
12	259.9809	258.7865	258.0530	264.3610	252.5665	258.2463	261.5941	260.2704	260.3056	262.9192
13	259.3652	257.5225	257.6802	259.2959	250.3630	256.3352	253.1854	258.4712	259.7373	260.2698
14	259.1447	257.5217	256.6920	257.9185	247.7903	253.2501	253.1542	258.4371	257.4130	258.5614
15	258.2988	255.3532	256.5284	256.2122	246.7848	249.7324	253.1033	256.1222	251.7414	257.8312
16	256.8063	251.5521	256.3782	254.1084	240.9671	248.9476	252.1502	255.4719	247.8253	256.8306
17	254.3325	245.9289	252.6668	251.0939	238.2357	248.6728	247.3773	249.9332	247.0834	254.7500
18	254.0470	242.2779	248.7465	250.9861	237.6748	229.4150	244.7763	249.4646	246.8815	250.0574
19	254.0074	233.6367	247.7135	249.7214	223.8156	227.4948	242.2756	243.4198	243.5030	248.2213
20	245.7423	230.5881	232.9170	242.2948	222.9927	227.3439	241.0987	240.2350	233.1188	247.5702

Appendix B3 – The results of 200 simulations in the asymmetric approach based on mean and extreme values

Appendix B3 – The results of 200 simulations in the asymmetric approach based on mean and extreme values

Iteration No.	Experiment No. 1	2	3	4	5	6	7	8	9	10
1	339.2883	281.5303	348.6791	380.1099	315.9045	321.0752	379.9515	279.9310	302.9648	271.7725
2	324.3264	278.4398	247.4805	355.2429	301.9732	306.7747	328.8698	261.1395	282.0482	264.8654
3	299.8740	273.7886	242.1910	343.4171	289.2172	270.1239	297.8799	258.9421	261.5993	261.8112
4	296.8535	261.3983	241.7891	331.8191	266.3941	249.6253	247.2050	258.0191	257.4377	252.0317
5	283.4745	250.8843	240.0771	297.0739	259.3226	249.6188	246.3913	256.8973	251.9829	228.5449
6	280.2598	243.9207	239.5568	256.9441	259.2523	234.1018	242.8137	256.7033	246.1061	224.1134
7	278.2092	242.1018	239.0772	253.1482	258.4826	232.0634	239.4795	239.7587	243.3247	222.6132
8	274.7929	226.7916	232.1727	244.8926	256.4392	225.5272	235.1800	234.0338	241.6084	221.0277
9	268.1012	226.6128	230.4529	243.2952	248.7355	225.3675	233.5470	233.4122	240.5384	217.2324
10	265.1183	226.2972	228.5120	242.4005	230.3818	221.2890	229.5688	232.4463	240.4687	212.2336
11	264.7994	222.0445	225.5851	238.6852	226.5849	220.6784	229.5319	230.1079	234.6947	212.0140
12	238.1774	218.8512	220.8386	225.9486	224.0902	217.6094	227.9921	226.8220	232.5411	209.3422
13	237.4297	216.6447	219.4366	216.1999	220.3833	215.9392	223.8679	223.3482	231.7322	208.5901
14	233.2241	216.4967	218.7776	214.1804	218.6604	214.6767	222.3195	222.1666	230.6328	208.3090
15	225.5851	215.9535	217.6035	214.1071	213.3121	212.6541	221.3109	220.5355	225.7278	205.0407
16	219.4366	213.9890	209.0607	212.5615	211.1925	211.3295	214.9404	211.6207	220.4002	202.7110
17	203.8770	211.7314	207.6664	210.5687	209.7539	205.8950	214.2434	204.9035	215.4279	201.9228
18	203.4848	209.9524	205.7158	209.9993	206.1161	203.1703	212.6105	204.4948	212.3378	199.8843
19	202.4414	208.7946	203.8770	209.4115	201.2268	202.2291	208.7794	204.0263	209.0848	198.5124
20	198.9663	193.4670	202.0099	203.4848	192.3154	191.4037	207.5843	190.6803	202.8990	194.0601

Appendix C – 121 fuzzy rules obtained by Wang-Mendel method in the best-found FIS

1. If (Aggressiveness is VLA) and (Impulsiveness is LI) and (Risk is LR) and (Self-assessment is MS) then (RTAs is VSNA)

2. If (Aggressiveness is VLA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is HS) then (RTAs is VSNA)

3. If (Aggressiveness is VLA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is MS) then (RTAs is VSNA)

4. If (Aggressiveness is VLA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is VHS) then (RTAs is MSNA) (1) '

5. If (Aggressiveness is LA) and (Impulsiveness is VLI) and (Risk is LR) and (Self-assessment is HS) then (RTAs is VSNA)

6. If (Aggressiveness is LA) and (Impulsiveness is VLI) and (Risk is MR) and (Self-assessment is MS) then (RTAs is VSNA)

7. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is LR) and (Self-assessment is VLS) then (RTAs is VSNA)

8. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is LR) and (Self-assessment is LS) then (RTAs is VSNA)

9. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is LR) and (Self-assessment is MS) then (RTAs is VSNA)

10. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is LR) and (Self-assessment is HS) then (RTAs is VSNA)

11. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is VLS) then (RTAs is VSNA)

12. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is LS) then (RTAs is VSNA)

13. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is MS) then (RTAs is VSNA)

14. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is HS) then (RTAs is VSNA)

15. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is VHS) then (RTAs is VSNA)

16. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is HR) and (Self-assessment is LS) then (RTAs is VSNA)

17. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is HR) and (Self-assessment is MS) then (RTAs is VSNA)

18. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is HR) and (Self-assessment is HS) then (RTAs is VSNA)

19. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is HR) and (Self-assessment is VHS) then (RTAs is SNA)

20. If (Aggressiveness is LA) and (Impulsiveness is LI) and (Risk is VHR) and (Self-assessment is MS) then (RTAs is VSNA)

21. If (Aggressiveness is LA) and (Impulsiveness is MI) and (Risk is LR) and (Self-assessment is VLS) then (RTAs is VSNA)

22. If (Aggressiveness is LA) and (Impulsiveness is MI) and (Risk is LR) and (Self-assessment is LS) then (RTAs is VSNA)

23. If (Aggressiveness is LA) and (Impulsiveness is MI) and (Risk is LR) and (Self-assessment is MS) then (RTAs is VSNA)

24. If (Aggressiveness is LA) and (Impulsiveness is MI) and (Risk is LR) and (Self-assessment is HS) then (RTAs is VSNA)

25. If (Aggressiveness is LA) and (Impulsiveness is MI) and (Risk is LR) and (Self-assessment is VHS) then (RTAs is VSNA)

26. If (Aggressiveness is LA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is LS) then (RTAs is MSNA)

27. If (Aggressiveness is LA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is MS) then (RTAs is SNA)

28. If (Aggressiveness is LA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is HS) then (RTAs is VSNA)

29. If (Aggressiveness is LA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is VHS) then (RTAs is VSNA)

30. If (Aggressiveness is LA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is MS) then (RTAs is MSNA)

31. If (Aggressiveness is LA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is HS) then (RTAs is MSNA)

32. If (Aggressiveness is LA) and (Impulsiveness is HI) and (Risk is LR) and (Self-assessment is MS) then (RTAs is VHNA)

33. If (Aggressiveness is LA) and (Impulsiveness is HI) and (Risk is LR) and (Self-assessment is HS) then (RTAs is MSNA)

34. If (Aggressiveness is LA) and (Impulsiveness is HI) and (Risk is MR) and (Self-assessment is VLS) then (RTAs is HNA)

35. If (Aggressiveness is LA) and (Impulsiveness is HI) and (Risk is MR) and (Self-assessment is LS) then (RTAs is MSNA)

36. If (Aggressiveness is LA) and (Impulsiveness is HI) and (Risk is MR) and (Self-assessment is HS) then (RTAs is MNA)

37. If (Aggressiveness is LA) and (Impulsiveness is HI) and (Risk is MR) and (Self-assessment is VHS) then (RTAs is SNA)

38. If (Aggressiveness is LA) and (Impulsiveness is HI) and (Risk is HR) and (Self-assessment is LS) then (RTAs is MSNA)

39. If (Aggressiveness is LA) and (Impulsiveness is HI) and (Risk is HR) and (Self-assessment is MS) then (RTAs is MSNA)

40. If (Aggressiveness is LA) and (Impulsiveness is HI) and (Risk is HR) and (Self-assessment is HS) then (RTAs is MSNA)

41. If (Aggressiveness is LA) and (Impulsiveness is VHI) and (Risk is LR) and (Self-assessment is VLS) then (RTAs is SNA)

42. If (Aggressiveness is LA) and (Impulsiveness is VHI) and (Risk is LR) and (Self-assessment is MS) then (RTAs is VSNA)

43. If (Aggressiveness is LA) and (Impulsiveness is VHI) and (Risk is MR) and (Self-assessment is MS) then (RTAs is VSNA)

44. If (Aggressiveness is LA) and (Impulsiveness is VHI) and (Risk is MR) and (Self-assessment is HS) then (RTAs is SNA)

45. If (Aggressiveness is LA) and (Impulsiveness is VHI) and (Risk is MR) and (Self-assessment is VHS) then (RTAs is VSNA)

46. If (Aggressiveness is LA) and (Impulsiveness is VHI) and (Risk is HR) and (Self-assessment is HS) then (RTAs is VSNA)

47. If (Aggressiveness is MA) and (Impulsiveness is VLI) and (Risk is LR) and (Self-assessment is HS) then (RTAs is VSNA)

48. If (Aggressiveness is MA) and (Impulsiveness is VLI) and (Risk is MR) and (Self-assessment is HS) then (RTAs is VSNA)

49. If (Aggressiveness is MA) and (Impulsiveness is LI) and (Risk is LR) and (Self-assessment is MS) then (RTAs is VSNA)

50. If (Aggressiveness is MA) and (Impulsiveness is LI) and (Risk is LR) and (Self-assessment is HS) then (RTAs is VSNA)

51. If (Aggressiveness is MA) and (Impulsiveness is LI) and (Risk is LR) and (Self-assessment is VHS) then (RTAs is SNA)

52. If (Aggressiveness is MA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is LS) then (RTAs is VSNA)

53. If (Aggressiveness is MA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is MS) then (RTAs is VSNA)

54. If (Aggressiveness is MA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is HS) then (RTAs is VSNA)

55. If (Aggressiveness is MA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is VHS) then (RTAs is VSNA)

56. If (Aggressiveness is MA) and (Impulsiveness is LI) and (Risk is HR) and (Self-assessment is MS) then (RTAs is VSNA)

57. If (Aggressiveness is MA) and (Impulsiveness is LI) and (Risk is HR) and (Self-assessment is HS) then (RTAs is MSNA)

58. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is LR) and (Self-assessment is LS) then (RTAs is MSNA)

59. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is LR) and (Self-assessment is MS) then (RTAs is MSNA)

60. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is LR) and (Self-assessment is HS) then (RTAs is VSNA)

61. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is LR) and (Self-assessment is VHS) then (RTAs is VSNA)

62. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is VLS) then (RTAs is MHNA)

63. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is LS) then (RTAs is SNA)

64. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is MS) then (RTAs is MSNA)

65. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is HS) then (RTAs is MSNA)

66. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is VHS) then (RTAs is MSNA)

67. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is VLS) then (RTAs is MHNA)

68. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is LS) then (RTAs is VSNA)

69. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is MS) then (RTAs is VSNA)

70. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is VHS) then (RTAs is MSNA)

71. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is VHR) and (Self-assessment is LS) then (RTAs is VSNA)

72. If (Aggressiveness is MA) and (Impulsiveness is MI) and (Risk is VHR) and (Self-assessment is VHS) then (RTAs is MSNA)

73. If (Aggressiveness is MA) and (Impulsiveness is HI) and (Risk is LR) and (Self-assessment is LS) then (RTAs is MNA)

74. If (Aggressiveness is MA) and (Impulsiveness is HI) and (Risk is LR) and (Self-assessment is MS) then (RTAs is VSNA)

75. If (Aggressiveness is MA) and (Impulsiveness is HI) and (Risk is MR) and (Self-assessment is LS) then (RTAs is VSNA)

76. If (Aggressiveness is MA) and (Impulsiveness is HI) and (Risk is MR) and (Self-assessment is MS) then (RTAs is VSNA)

77. If (Aggressiveness is MA) and (Impulsiveness is HI) and (Risk is MR) and (Self-assessment is VHS) then (RTAs is MNA)

78. If (Aggressiveness is MA) and (Impulsiveness is HI) and (Risk is HR) and (Self-assessment is VLS) then (RTAs is MHNA)

79. If (Aggressiveness is MA) and (Impulsiveness is HI) and (Risk is HR) and (Self-assessment is LS) then (RTAs is MNA)

80. If (Aggressiveness is MA) and (Impulsiveness is HI) and (Risk is HR) and (Self-assessment is HS) then (RTAs is MSNA)

81. If (Aggressiveness is MA) and (Impulsiveness is VHI) and (Risk is LR) and (Self-assessment is VLS) then (RTAs is MHNA)

82. If (Aggressiveness is MA) and (Impulsiveness is VHI) and (Risk is MR) and (Self-assessment is VLS) then (RTAs is MNA)

83. If (Aggressiveness is MA) and (Impulsiveness is VHI) and (Risk is MR) and (Self-assessment is MS) then (RTAs is MSNA)

84. If (Aggressiveness is HA) and (Impulsiveness is VLI) and (Risk is HR) and (Self-assessment is HS) then (RTAs is MSNA)

85. If (Aggressiveness is HA) and (Impulsiveness is LI) and (Risk is VLR) and (Self-assessment is LS) then (RTAs is MSNA)

86. If (Aggressiveness is HA) and (Impulsiveness is LI) and (Risk is LR) and (Self-assessment is LS) then (RTAs is VSNA)

87. If (Aggressiveness is HA) and (Impulsiveness is LI) and (Risk is LR) and (Self-assessment is HS) then (RTAs is MSNA)

88. If (Aggressiveness is HA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is LS) then (RTAs is VSNA)

89. If (Aggressiveness is HA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is MS) then (RTAs is VSNA)

90. If (Aggressiveness is HA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is HS) then (RTAs is MSNA)

91. If (Aggressiveness is HA) and (Impulsiveness is LI) and (Risk is MR) and (Self-assessment is VHS) then (RTAs is MSNA)

92. If (Aggressiveness is HA) and (Impulsiveness is LI) and (Risk is HR) and (Self-assessment is LS) then (RTAs is MSNA)

93. If (Aggressiveness is HA) and (Impulsiveness is LI) and (Risk is HR) and (Self-assessment is MS) then (RTAs is MHNA)

94. If (Aggressiveness is HA) and (Impulsiveness is LI) and (Risk is HR) and (Self-assessment is HS) then (RTAs is MSNA)

95. If (Aggressiveness is HA) and (Impulsiveness is LI) and (Risk is VHR) and (Self-assessment is LS) then (RTAs is MSNA)

96. If (Aggressiveness is HA) and (Impulsiveness is MI) and (Risk is LR) and (Self-assessment is MS) then (RTAs is VSNA)

97. If (Aggressiveness is HA) and (Impulsiveness is MI) and (Risk is LR) and (Self-assessment is HS) then (RTAs is MSNA)

98. If (Aggressiveness is HA) and (Impulsiveness is MI) and (Risk is LR) and (Self-assessment is VHS) then (RTAs is VSNA)

99. If (Aggressiveness is HA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is VLS) then (RTAs is MNA)

100. If (Aggressiveness is HA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is MS) then (RTAs is MSNA)

101. If (Aggressiveness is HA) and (Impulsiveness is MI) and (Risk is MR) and (Self-assessment is HS) then (RTAs is MSNA)

102. If (Aggressiveness is HA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is VLS) then (RTAs is MSNA)

103. If (Aggressiveness is HA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is LS) then (RTAs is MSNA)

104. If (Aggressiveness is HA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is MS) then (RTAs is SNA)

105. If (Aggressiveness is HA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is HS) then (RTAs is MSNA)

106. If (Aggressiveness is HA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is VHS) then (RTAs is MSNA)

107. If (Aggressiveness is HA) and (Impulsiveness is MI) and (Risk is VHR) and (Self-assessment is HS) then (RTAs is SNA)

108. If (Aggressiveness is HA) and (Impulsiveness is HI) and (Risk is LR) and (Self-assessment is VLS) then (RTAs is HNA)

109. If (Aggressiveness is HA) and (Impulsiveness is HI) and (Risk is LR) and (Self-assessment is LS) then (RTAs is MNA)

110. If (Aggressiveness is HA) and (Impulsiveness is HI) and (Risk is MR) and (Self-assessment is VLS) then (RTAs is VHNA)

111. If (Aggressiveness is HA) and (Impulsiveness is HI) and (Risk is MR) and (Self-assessment is LS) then (RTAs is MSNA)

112. If (Aggressiveness is HA) and (Impulsiveness is HI) and (Risk is MR) and (Self-assessment is MS) then (RTAs is MSNA)

113. If (Aggressiveness is HA) and (Impulsiveness is HI) and (Risk is MR) and (Self-assessment is HS) then (RTAs is MSNA)

114. If (Aggressiveness is HA) and (Impulsiveness is HI) and (Risk is MR) and (Self-assessment is VHS) then (RTAs is MSNA)

115. If (Aggressiveness is HA) and (Impulsiveness is HI) and (Risk is HR) and (Self-assessment is VLS) then (RTAs is VHNA)

116. If (Aggressiveness is HA) and (Impulsiveness is HI) and (Risk is HR) and (Self-assessment is LS) then (RTAs is HNA)

117. If (Aggressiveness is HA) and (Impulsiveness is HI) and (Risk is HR) and (Self-assessment is MS) then (RTAs is MHNA)

118. If (Aggressiveness is HA) and (Impulsiveness is HI) and (Risk is HR) and (Self-assessment is HS) then (RTAs is MSNA)

119. If (Aggressiveness is VHA) and (Impulsiveness is MI) and (Risk is HR) and (Self-assessment is HS) then (RTAs is MSNA)

120. If (Aggressiveness is VHA) and (Impulsiveness is HI) and (Risk is HR) and (Self-assessment is MS) then (RTAs is MHNA)

121. If (Aggressiveness is VHA) and (Impulsiveness is HI) and (Risk is HR) and (Self-assessment is HS) then (RTAs is MHNA)