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A Decision-Making Model for Professional Drivers Selection: A Hybridized Fuzzy–AROMAN–Fuller Approach

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Abstract: Professional drivers play a crucial role in many businesses and the lives of people. They are responsible for transferring people and goods between distant points, enabling safe and efficient flows. The road traffic death rate is from 8.3 to 27.5 per 100,000 inhabitants in the countries globally. Because professional drivers spend a significant amount of time on the road, their appropriate selection may contribute to general traffic safety. In addition, an adequate selection of candidates significantly impacts the financial costs of the employing company. However, the recruitment procedure is a very complex task where multiple criteria should be considered. By its nature, this is a typical multi-criteria decision-making problem. The purpose of this paper is twofold: to contribute to the methodological, as well as to the professional field. Considering the professional, we propose a decision-making tool in the procedure of professional driver selection. There are several methodological contributions. By reviewing the literature, we identified 14 criteria for candidate selection. In the proposed model, by using expert opinion and implementing DEMATEL and Fuller's pairwise comparisons, we ranked these criteria and determined the seven most important for further calculation procedure. Here, we introduced an original approach for measuring the reliability of obtained answers. Then, to rank the candidates, the fuzzy AROMAN approach is applied for the first time in the literature. The input data were obtained in the form of a survey, where the experts evaluated the importance of criteria and their interrelation. We used MS Excel and MATLAB for data processing. An additional methodological contribution of this study is an advancement of the AROMAN method by the proposal of an algorithm for the calculation of parameter λ used in the final ranking formula. To illustrate the applicability of the proposed model, a case study is provided. Based on the results, we can conclude that the new methodological approaches can be successfully used in the procedure of professional driver selection, as well as in solving other multi-criteria decision-making problems.

Keywords: recruitment procedure; personnel selection; road safety; transportation companies; professional drivers; fuzzy logic; AROMAN; Fuller's triangle; DEMATEL

MSC: 03E72; 47S40; 90B50

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1. Introduction

Road traffic accidents are one of the leading causes of death and serious injuries for people all across the world. Based on a report by the World Health Organization, the road traffic death rate is from 8.3 in high-income countries, to 27.5 per 100,000 inhabitants in low- and middle-income countries. In total, there are around 1.35 million deaths and 50 million injured on the roads each year [1]. Many problems in transportation, such as traffic congestion, road blockage, and road accidents, can be solved to a certain extent by the digitization of roads and vehicles [2]; however, the impact of the human factor is still of crucial importance as well. In the literature, there are three main categories of factors that contribute to road traffic accident occurrence: human factors, vehicle factors, and the factor related to road design and construction. Human factors are by far the most represented cause of accidents. Around 90 to 95% of all traffic accidents involve human error [3–5]. Based on this, it is evident that adequate educational programs for drivers can contribute to improved traffic safety. In addition, particular attention should be placed on the recruitment procedures for professional drivers having in mind their constant and widespread presence on the roads.

A professional driver represents a driver who drives a transport vehicle as a paid employee. In this study, we are focused on road transport, and the case study is related to bus drivers. However, the proposed methodology is general and can be implemented for other types of drivers, such as truck drivers, train drivers, sea captains, or airline pilots, as well as in general cases, for any personnel selection problem.

Professional drivers, depending on the type of driving vehicle, are responsible for goods of high value that are transported, and even more importantly, for the lives of people that travel by different means of public transport. This job is very demanding, both from the physical and mental standpoint [6]. These are the reasons why particular attention should be placed on the selection procedure, to employ candidates that are capable of responding to all of the challenges of this work. It is evident that various criteria influence the assessment procedure of candidates and one of the aims of this paper is to investigate the literature and systemize the criteria used in the process of professional driver selection.

The main aim of this paper is to propose a methodological framework for solving the problem of professional driver selection. Having in mind, on the one hand, that certain criteria should be minimized or maximized in decision-making depending on their nature, and on the other hand, that the candidates can be considered as alternatives, it can be concluded that this is a typical multi-criteria decision-making (MCDM) problem. There are numerous MCDM techniques in the literature [7–9]; however, to contribute both to the professional and scientific fields, we propose an extension of a relatively new MCDM method: An alternative ranking order method accounting for two-step normalization—AROMAN [10,11]. Because certain criteria in the process of professional driver selection are hard to describe numerically, we introduce fuzzy logic in the model. The main motive for applying the AROMAN method is that it is a very new MCDM method and we intend to further test its applicability. Aside from this, our crucial goal is to test this method in a fuzzy environment. Therefore, the main contribution of this study can be structured as follows: (i) We identified the criteria for the selection of professional drivers by a comprehensive literature review, (ii) We measured the relevance ranks of the set criteria by interviewing the experts from the field and by implementing Fuller's triangle method, (iii) We implemented the AROMAN method in the fuzzy environment for the first time in the literature, (iv) We proposed an extension of the AROMAN method by integrating the relevance ranks of the set criteria obtained by Fuller's triangle method with the calculation of alternatives ranks.

The rest of the paper is structured as follows: Section 2 is a review of the literature to identify the criteria for professional driver selection. Section 3 explains the methodology of the research. To illustrate the applicability of the proposed model, in Section 4 there is an illustrative case study. Finally, Section 5 represents a conclusion.

2. Literature Review

This section investigates the current knowledge in the field of professional drivers. The main research source for this study was the Web of Science (WoS) database. There are two subsections. The first is related to the review of different topics considered in this field and the second is devoted to the identification of criteria used for the professional driver evaluation.

2.1. Literature on Professional Drivers

In the last decade, there have been numerous papers addressing the issue of professional drivers. Here, we will mention just a few to demonstrate the diversity of considered problems in the field. For instance, Zaranka et al. [12] evaluated the factors affecting the behavior of road users and investigated the impact of fatigue on road users. Maslać et al. [13] compared the behaviors of professional and non-professional drivers in the Republic of Serbia. Rosso et al. [14] conducted a cross-sectional questionnaire survey to investigate obesity among professional drivers in Italy. Chen et al. [15] investigated the difference between professional and non-professional drivers in terms of the effectiveness of the compensatory strategy adopted by older drivers. Wu et al. [16] carried out research related to the effectiveness of eco-driving training for male professional and non-professional drivers.

Öz et al. [17] considered professional and non-professional drivers' stress reactions and risky driving. Nordfaern et al. [18] investigated safety attitudes, behavior, anxiety, and perceived control among professional and non-professional drivers. Serrano-Fernández et al. [19] addressed the most important predictive variables for sleep quality in professional drivers. Chen et al. [20] conducted a driving simulator study regarding the safety of professional drivers in an aging society. Meng et al. [21] investigated driving fatigue in professional taxi and truck drivers in Beijing. Han and Jianyou [22] tackled driver behavior and traffic accident involvement among professional urban bus drivers in China. Hernández-Rodríguez et al. [23] estimated psychosocial risk and job satisfaction in professional drivers. Serrano-Fernández et al. [24] considered variables that predict attitudes toward safety regulations in professional drivers. Llamazares et al. [25] investigated commuting accidents of Spanish professional drivers when the occupational risk exceeds the workplace. The related research papers are summarized in Table 1.

Table 1. Studies related to professional drivers.

Year	Authors	Considered Problem
2010	Öz, Özkan and Lajunen [17]	Professional and non-professional drivers' stress reactions and risky driving
2012	Nordfaern, Jorgensen and Rundmo [18]	Safety attitudes, behavior, anxiety, and perceived control among professional and non-professional drivers
2015	Rosso, Perotto, Feola, Bruno and Caramella [14]	Obesity among professional drivers
2015	Meng, Li, Cao, Li, Peng, Wang and Zhang [21]	Driving fatigue among professional taxi and truck drivers
2018	Maslać, Antić, Lipovac, Pešić and Milutinović [13]	Comparison of the professional and non-professional drivers considering rules violations
2018	Wu, Zhao, Rong and Zhang [16]	Effectiveness of eco-driving training for male professional and non-professional drivers
2019	Chen, Sze and Bai [20]	Safety of professional drivers in an ageing society
2020	Han and Zhao [22]	Driver behavior and traffic accident involvement among professional urban bus drivers in China
2020	Serrano-Fernández, Tàpia-Caballero, Boada-Grau and Araya-Castillo [24]	Variables that predict attitudes toward safety regulations in professional drivers
2021	Zaranka, Pečeliunas and Žuraulis [12]	Factors affecting the behavior of road users
2021	Serrano-Fernández, Boada-Grau, Robert-Sentís and Vigil-Colet [19]	Predictive variables for sleep quality in professional drivers
2021	Chen, Sze, Newnam and Bai [15]	Difference between professional and non-professional drivers in terms of the effectiveness
2021	Llamazares, Useche, Montoro and Alonso [25]	Commuting accidents of professional drivers when the occupational risk exceeds the workplace
2022	Hernández-Rodríguez, Maeso-González, Gutiérrez-Bedmar and García-Rodríguez [23]	Psychosocial risk and job satisfaction in professional drivers

As can be noticed from this part of the literature review, various forms of studies tackling professional drivers have been conducted by researchers around the globe. However, the research gap in the literature is that there is a lack of studies considering the professional driver evaluation and selection problem. Having the stated in mind, this paper aims to address the professional driver evaluation and selection issue using a multicriteria decision-making approach combined with fuzzy logic. More concretely, this paper applies the recently developed AROMAN method, coupled with the fuzzy logic to effectively evaluate and select the most appropriate professional driver. As a starting point to perform this procedure, the evaluation criteria should be set. The next subchapter is devoted to this task, where the criteria are identified by the review of current publications.

2.2. Criteria for Professional Drivers Evaluation

In this subsection, a summarized overview of the considered criteria for professional driver evaluation is offered, along with the applied methodology in the related papers (Table 2). Professional drivers need to maintain their attention on many traffic circumstances while driving. Cvahte Ojsteršek and Topolšek [26] analyzed the influence of drivers' visual and cognitive attention on their perception of changes in the traffic environment. Further, Milošević and Gajić [27] considered how different situations in traffic impacts the perception of road signs.

Table 2. Criteria for professional driver evaluation.

No.	Criteria	Authors	Used Methodology
1.	Attention	- Cvahte Ojsteršek and Topolšek [26] - Milošević and Gajić [27]	- Statistical analysis - Statistical analysis
2.	Fatigue resistance	- Milosevic [28] - Brown, Farias Zuniga, Mulla, Mendonca, Keir and Bray [29]	- Statistical analysis - Statistical analysis
3.	Reaction time	- Poliak, Svabova, Benus and Demirci [30] - Čulík, Kalašová and Štefancová [31]	- Statistical analysis - Statistical analysis
4.	Visual abilities	- Anstey, Horswill, Wood and Hatherly [32] - Lacherez, Au and Wood [33]	- Statistical analysis - Statistical analysis
5.	Speed estimation	- Chen, Wei and Gao [34] - Čubranić-Dobrodolac, Švadlenka, Čičević, Trifunović and Dobrodolac [35]	- Fuzzy AHP - Fuzzy inference system
6.	Physical fitness	- Caragata, Tuokko and Damini [36] - Gilson, Mielke, Coombes, Feter, Smith, Duncan, Wallis and Brown [37]	- Statistical analysis - Statistical analysis
7.	Driving experience	- Ku Khalif, Gegov and Abu Bakar [38] - Mueller and Trick [39]	- Fuzzy TOPSIS - Statistical analysis
8.	Risk assessment	- Wang, Chen, Chen, Deng, Chen [40] - Al-Garawi, Dalhat and Aga [41]	- Statistical analysis - Statistical analysis
9.	Impulsiveness	- Cubranic-Dobrodolac, Svadlenka, Markovic and Dobrodolac [42] - Smorti and Guarnieri [43]	- Fuzzy inference system - Statistical analysis
10.	Aggressiveness	- Cubranic-Dobrodolac, Svadlenka, Markovic and Dobrodolac [42] - Rodriguez Gonzalez, Wilby, Vinagre Diaz and Sanchez Avila [44]	- Fuzzy inference system - Statistical analysis
11.	Self-assessment of driving ability	- Tronsmoen [45] - Sundström [46]	- Statistical analysis - Statistical analysis
12.	Space capabilities	- Čubranić-Dobrodolac, Švadlenka, Čičević, Trifunović and Dobrodolac [47]	- Fuzzy inference system
13.	Intelligence	- Petrović and Petrović [48] - Li, Lai and Kao [49]	- Fuzzy TOPSIS - TOPSIS
14.	Morality	- Zaranka, Pečeliunas and Žuraulis [12] - Li, Lai and Kao [49]	- Statistical analysis - TOPSIS

Milosevic [28] examined the fatigue resistance in a group of city bus drivers, by measuring heart rate by electro-cardio recorder before and after driving. It is interesting to notice that mental fatigue can cause negative effects on physical performance as well [29].

Drivers' reaction time is related to the amount of time needed to process important information and act in emergencies. Poliak et al. [30] evaluated the impact of age on the reaction time of professional drivers. Čulík et al. [31] investigated if gender, practice, or alcohol significantly affected the reaction time of drivers.

Anstey et al. [32] proposed a model to measure the capacity to drive safely based on assessing visual functions. Lacherez et al. [33] examined an association between indices of driving safety and low-level changes in visual function.

Papers that deal with the selection procedure of professional drivers by using a multi-criteria decision-making approach are very rare in the literature. One of them is by Chen et al. [34] where speed estimation is taken as an evaluation criterion. The research by Čubranić-Dobrodolac et al. [35] confirms that a level of speed perception capabilities is related to the occurrence of road traffic accidents.

In the literature, an interdependence between physical fitness and driving skills is proven [36]. Since professional drivers often drive even during the night, resulting in a lack of sleep, this segment is of particular importance in the selection procedure [37].

Inexperience is one of the strongest predictors of crashes [39]. Therefore, work experience is often taken as an evaluation criterion in the staff recruitment process [38], as well as risk assessment [40]. Driver's improper driving behavior is often related to poor risk assessment [40,41].

Examples of driver aggression are related to driving at excessive speed, intimidation of other road users, improper following, improper lane changing and passing, and similar. It is proven that aggressiveness positively correlates with road accident occurrence [42,44].

Aside from aggression, similar behavior represents impulsiveness. There is evidence in the literature that elevated impulsiveness is associated with other forms of inappropriate behavior in traffic, such as drink-driving, drug-driving offenses, using a mobile phone behind the wheel, etc. [43,50].

A higher level of self-assessment of driving ability can be found in drivers with a lower level of involvement in crashes [45]. A comprehensive review of methods for measuring subjective driving ability can be found in [46]. Another ability that contributes to safe driving relates to space assessment capability [47].

Intelligence is an innate ability that is very often considered in the recruitment procedure, in the field of transportation, and many others [48,49]. Zaranka et al. [12] introduce a social component in the recruitment procedure of professional drivers, where the first things considered are morality, social fit, and interpersonal skills [49,51].

3. Methods

After an extensive literature review to identify criteria for professional driver evaluation, further research methodology can be structured into two parts. The first aim of reducing the number of identified criteria to simplify the calculation process in the second part relates to the ranking of candidates. In the first part, we apply two methods, DEMATEL and the Fuller triangle method. Interdependence between the criteria is calculated by DEMATEL, while the level of importance of each criterion to the decision-making process is determined by the Fuller triangle method. The second part of the methodology is related to the proposal of the Fuzzy–AROMAN–Fuller approach for ranking the alternatives. The research structure is presented in Figure 1.

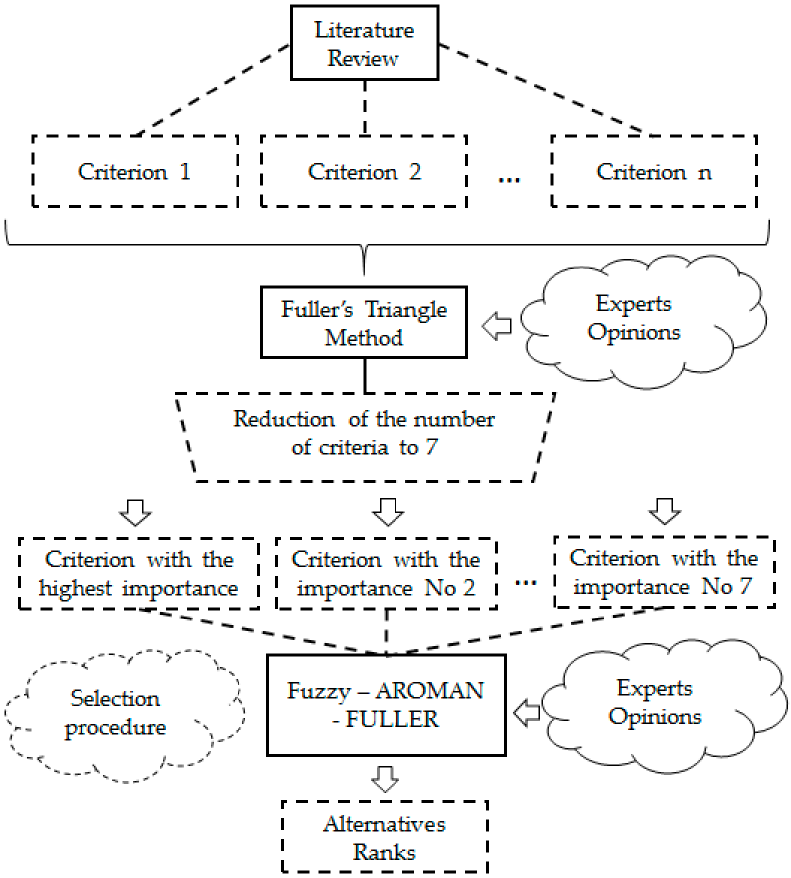

Figure 1. Research structure.

3.1. Determination of Interdependence between the Criteria by the DEMATEL Method

The DEMATEL method can be structured into four main steps. They relate to generating the direct-relation matrix by interviewing the experts, normalization of the direct-relation matrix, calculating the total-relation matrix, and producing a causal diagram. In the following text, the procedure is explained in more detail.

Step 1. *Generate the direct-relation matrix.*

The direct-relation matrix is created by using a comparison scale:

- 0 = No influence;
- 1 = Low influence;
- 2 = Medium influence;
- 3 = High influence;
- 4 = Very high influence.

An expert answers the questions considering the degree of influence of one criterion over another. Let a_{ij} denotes a pair-wise comparison score between two criteria. If there are n criteria, and all the comparisons are obtained, the direct-relation matrix $A = [a_{ij}]_{nxn}$ can be formed. If there are more experts $A^1, A^2, \ldots, A^m$, the final direct-relation matrix can be generated by Equation (1) [52].

$$A = \frac{1}{m}\sum_{k=1}^{m} A_{ij}^{k} \tag{1}$$

Step 2. *Normalize the direct-relation matrix.*

The normalized direct-relation matrix X, $X = [x_{ij}]_{nxn}$ and $0 \leq x_{ij} \leq 1$, can be calculated by Equations (2) and (3). It should be noted that all diagonal elements are equal to zero [52].

$$X = S * A \tag{2}$$

$$S = \frac{1}{\max\limits_{1 \le i \le n} \sum_{j=1}^{n} A_{ij}}, i, j = 1, 2, \ldots, n \tag{3}$$

Step 3. *Calculate the total-relation matrix.*

The total-relation matrix T can be obtained by applying Equation (4). Here, the matrix I indicates the identity matrix [52].

$$T = X * (I - X)^{-1} \tag{4}$$

Step 4. *Create a causal diagram.*

To interpret the results, the important variables are D and R. They are calculated by Equations (6) and (7) [52].

$$T = t_{ij},\ i, j = 1, 2, \ldots, n \tag{5}$$

$$D = \sum_{j=1}^{n} t_{ij} \tag{6}$$

$$R = \sum_{i=1}^{n} t_{ij} \tag{7}$$

A causal diagram can be obtained by mapping the pairs ($D + R$, $D - R$). The first dimension gives information about the impact of a particular criterion over others, while the second dimension describes the nature of this impact, i.e., is a criterion in the cause (positive values) or effect group (negative values).

3.2. Determination of the Criteria Relevance by the Fuller Triangle Method

To reduce the number of criteria identified by the literature review, we will determine their relevance and rank them according to the method named the Fuller triangle method [53–55]. The Fuller method is in the group of the subjective weighting methods, such as the Analytic Hierarchy Process—AHP [56], Best–Worst Method—BWM [57], Full Consistency Method—FUCOM [58], or Stepwise Weight Assessment Ratio Analysis—SWARA [59]. The procedure of the Fuller triangle method is explained in the following text.

Step 1. *The Fuller method starts with forming a triangular structure as shown in Figure 2. The first two rows relate to the pairwise comparison of Criterion 1 with all other criteria. Accordingly, in the first row, there are $n - 1$ columns with Criterion 1 and the same number of all other criteria from Criterion 2 to n. A decision maker should choose which of the considered criteria in each pair is more important than the other and mark it. The same procedure should be performed for all other comparisons; however, each of the subsequent two rows is shorter by one column, and at the end, there is just a comparison of one pair, between Criterion $n - 1$ and n. The number of all pairs being compared is equal to N, calculated by Equation (8), where n is the total number of compared criteria.*

$$N = \frac{n(n-1)}{2} \tag{8}$$

Step 2. *After all comparisons are carried out, it can be considered that each criterion that "win" as the more important one in the pairwise comparison receives one point. If a decision is made that they are of equal significance, the criteria achieve half of a point each. The points awarded to criteria should be summed up per each criterion, and the sums represent their relevance rank.*

Step 3. *In the third step, the relevance ranks (w_j) should be normalized according to Equation (9) [53]. v_j represents the number of preferences, i.e., the number of points each criterion received, and in the denominator is the total number of all preferences.*

$$w_j = \frac{v_j}{\sum_{k=1}^{n} v_k};\ j = 1, 2, \ldots, n \tag{9}$$

Step 4. *If there is a criterion that did not receive any points, in this case, in the previous formula, the numerator should be increased by 1 to avoid the relevance rank being equal to zero. Then, the relevance ranks should be calculated by Equation (10).*

$$w_j = \frac{v_j + 1}{n + \sum_{k=1}^{n} v_k};\ j = 1, 2, \ldots, n \tag{10}$$

If the evaluation of relevance ranks is carried out by more than one expert, an arithmetic mean value of all input values should be calculated. To aggregate opinions from more experts, other methods can be used as well, such as geometric mean [60] or centroid [61]. However, the arithmetic mean is the most commonly used.

C1 C2	C1 C3	C1 C4	…. …	C1 Cn
C2 C3	C2 C4	… …	C2 Cn	
…	…			
…	…			
Cn-2 Cn-1	Cn-2 Cn			
Cn-1 Cn				

Figure 2. Illustration of starting procedure in Fuller triangle method.

An important issue considering subjective methods, such is the Fuller triangle method, is measuring the reliability of collected answers. For example, in the AHP method, there is a well-known approach where the rate of inconsistency is calculated, and it should be lower than 0.1 to conclude satisfactory reliability. However, this approach cannot be applied in the case of the Fuller triangle method, and in addition, by reviewing the literature, we did not find any convenient approach that could be implemented here. This was an inspiration for the authors to propose a new technique to assess the reliability of experts' opinions.

The procedure implies a second round of interviewing the experts. Without knowing the results of the first round where they gave opinions about the pair-wise comparisons of criteria importance, they were asked to give additional assessments. They were told to imagine the scale from 0 to 100% and to determine the percentage importance of each criterion for the recruitment process of selecting the professional driver. This should be carried out in the way that all 14 assessments give the sum of 100%. Finally, the results of the second round should be compared with the first round to conclude about the reliability of answers. If we denote the answers from the second round by p_j, and previously we marked the obtained weight in the first round by w_j, then the rate of inconsistency (*RI*) can be calculated as explained in Equation (11).

$$RI = \frac{\sum_{j=1}^{n} \left| w_j * 100 - p_j \right|}{100} \tag{11}$$

3.3. Ranking Alternatives Using a Hybridized Fuzzy-AROMAN-FULLER Approach

As previously mentioned, the AROMAN method is for the first time implemented in a fuzzy environment in this paper. Therefore, it is useful to provide some preliminaries on fuzzy arithmetic.

3.3.1. Preliminaries on Fuzzy Arithmetic

In the following text, we briefly present some basic definitions of fuzzy sets and numbers [62].

Definition 1. *A fuzzy set $\widetilde{A}$ in a universe of discourse X is characterized by a membership function $\mu_{\widetilde{A}}(x)$ which associates with each element x in X a real number in the interval* $[0,1]$. *The function value $\mu_{\widetilde{A}}(x)$ represents the grade of membership of x in $\widetilde{A}$ [62].*

Definition 2. *A fuzzy set $\widetilde{A}$ of the universe of discourse X is convex if and only if for all x_1, x_2 in X,*

$$\mu_{\widetilde{A}}(\gamma x_1 + (1-\gamma)\, x_2) \geq \mathrm{Min}\,(\mu_{\widetilde{A}}(x_1),\ \mu_{\widetilde{A}}\,(x_2)), \tag{12}$$

where $\in [0,1]$ *[62].*

Definition 3. *A fuzzy set $\widetilde{A}$ of the universe of discourse X is called a normal fuzzy set implying that $\exists\, x_i \in X$, $\mu_{\widetilde{A}}\,(x_i) = 1$ [62].*

Definition 4. *A fuzzy number is a fuzzy subset in the universe of discourse X that is both convex and normal. An example of a triangular fuzzy number is given in Figure 3.*

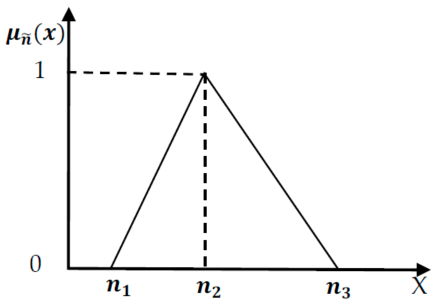

Figure 3. A triangular fuzzy number $\widetilde{n}$.

Definition 5. *The α-cut of fuzzy number $\widetilde{n}$ is defined*

$$\widetilde{n}^{\alpha} = \left\{x_i : \mu_{\widetilde{n}}(x_i) \geq \alpha, x_i \in X\right\}, \tag{13}$$

where $\alpha \in [0,1]$ *[62].*

$\widetilde{n}^{\alpha}$ is a non-empty bounded closed interval contained in X and it can be denoted by $\widetilde{n}^{\alpha} = \left[\widetilde{n}_l^{\alpha}, \widetilde{n}_u^{\alpha}\right]$, where $\widetilde{n}_l^{\alpha}$ and $\widetilde{n}_u^{\alpha}$ are the lower and upper bounds of the closed interval, respectively. Figure 4 shows a fuzzy number $\widetilde{n}$ with α-cuts, where

$$\widetilde{n}^{\alpha 1} = \left[\widetilde{n}_l^{\alpha 1}, \widetilde{n}_u^{\alpha 1}\right],\ \widetilde{n}^{\alpha 2} = \left[\widetilde{n}_l^{\alpha 2}, \widetilde{n}_u^{\alpha 2}\right]. \tag{14}$$

From Figure 4 we can see that if $\alpha_2 \geq \alpha_1$, then $\widetilde{n}_l^{\alpha 2} \geq \widetilde{n}_l^{\alpha 1}$ and $\widetilde{n}_u^{\alpha 1} \geq \widetilde{n}_u^{\alpha 2}$.

Definition 6. *A triangular fuzzy number $\widetilde{n}$ can be defined by a triplet (n_1, n_2, n_3) shown in Figure 3. The membership function $\mu_{\widetilde{n}}(x)$ is defined as [62]:*

$$\mu_{\widetilde{n}}(x) = \begin{cases} 0, \ x < n_1 \\ \frac{x-n_1}{n_2-n_1}, \ n_1 \le x \le n_2 \\ \frac{n_3-x}{n_3-n_2}, \ n_2 \le x \le n_3 \\ 0, \ x > n_3 \end{cases} \tag{15}$$

Definition 7. *If $\widetilde{n}$ is a fuzzy number and $\widetilde{n}_l^{\alpha} > 0$ for $\alpha \in [0,1]$, then $\widetilde{n}$ is called a positive fuzzy number.*

Given any two positive fuzzy numbers $\widetilde{m}$, $\widetilde{n}$ and a positive real number r, the α-cut of two fuzzy numbers are $\widetilde{m}^{\alpha} = [m_l^{\alpha}, m_u^{\alpha}]$ and $\widetilde{n}^{\alpha} = [n_l^{\alpha}, n_u^{\alpha}]$ ($\alpha \in [0,1]$), respectively. According to the interval of confidence, some main operations of positive fuzzy numbers $\widetilde{m}$ and $\widetilde{n}$ can be expressed as follows [62]:

$$\left(\widetilde{m}(+)\widetilde{n}\right)^{\alpha} = [m_l^{\alpha} + n_l^{\alpha}, m_u^{\alpha} + n_u^{\alpha}], \tag{16}$$

$$\left(\widetilde{m}(-)\widetilde{n}\right)^{\alpha} = [m_l^{\alpha} - n_u^{\alpha}, m_u^{\alpha} - n_l^{\alpha}], \tag{17}$$

$$\left(\widetilde{m}(\cdot)\widetilde{n}\right)^{\alpha} = [m_l^{\alpha} \cdot n_l^{\alpha}, m_u^{\alpha} \cdot n_u^{\alpha}], \tag{18}$$

$$\left(\widetilde{m}(:)\widetilde{n}\right)^{\alpha} = \left[\frac{m_l^{\alpha}}{n_u^{\alpha}}, \frac{m_u^{\alpha}}{n_l^{\alpha}},\right], \tag{19}$$

$$\left(\widetilde{m}^{\alpha}\right)^{-1} = \left[\frac{1}{m_u^{\alpha}}, \frac{1}{m_l^{\alpha}},\right], \tag{20}$$

$$\left(\widetilde{m}(\cdot)r\right)^{\alpha} = [m_l^{\alpha} \cdot r, m_u^{\alpha} \cdot r], \tag{21}$$

$$\left(\widetilde{m}(:)r\right)^{\alpha} = \left[\frac{m_l^{\alpha}}{r}, \frac{m_u^{\alpha}}{r},\right], \tag{22}$$

where r is a constant.

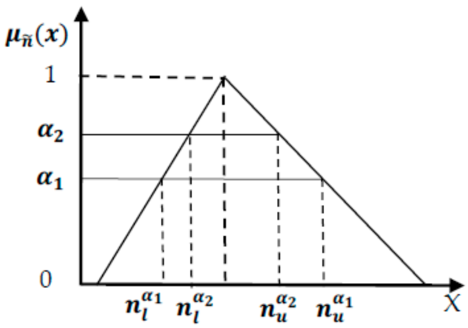

Figure 4. Fuzzy number $\widetilde{n}$ with α cuts.

3.3.2. Fuzzy–AROMAN–Fuller Approach

An extension of the AROMAN method [10,11] to the fuzzy environment is proposed in this part. The method is very convenient for solving MCDM problems where more experts are involved in the decision-making process. The procedure will be explained in steps.

Step 1. *Determine the initial decision-making matrix with the input data.*

A fuzzy MCDM problem can be presented in matrix format as:

$$\widetilde{D} = \begin{bmatrix} \widetilde{x}_{11} & \cdots & \widetilde{x}_{1j} & \cdots & \widetilde{x}_{1n} \\ \widetilde{x}_{21} & \cdots & \widetilde{x}_{2j} & \cdots & \widetilde{x}_{2n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{x}_{m1} & \cdots & \widetilde{x}_{mj} & \cdots & \widetilde{x}_{mn} \end{bmatrix}, \; i = 1, 2, \ldots, m, j = 1, 2, \ldots, n.$$

where $\widetilde{x}_{ij}$ are linguistic variables.

To rate the qualitative criteria, the inputs are linguistic variables. These linguistic variables can be expressed as triangular fuzzy numbers. The scale is offered in Table 3.

Table 3. Linguistic variables for the ratings of criteria.

Linguistic Variable	Fuzzy Number
Very low (VL)	(0,0,1)
Low (L)	(0,1,3)
Medium-low (ML)	(1,3,5)
Medium (M)	(3,5,7)
Medium-high (MH)	(5,7,9)
High (H)	(7,9,10)
Very High (VH)	(9,10,10)

If there are K experts that evaluate the alternatives based on set criteria, then the ratings can be calculated as:

$$\widetilde{x}_{ij} = \frac{1}{K}\left[\widetilde{x}^{1}_{ij}(+)\widetilde{x}^{2}_{ij}(+)\ldots(+)\widetilde{x}^{K}_{ij}\right]. \tag{23}$$

In the further procedure, the normalization of data should be carried out. The AROMAN method implies two types of normalization, as explained in Steps 2 and 3.

Step 2. *Normalization No. 1.*

$$\widetilde{t}_{ij} = \frac{\widetilde{x}_{ij} - \min\limits_{i} \widetilde{x}_{ij}}{\max\limits_{i} \widetilde{x}_{ij} - \min\limits_{i} \widetilde{x}_{ij}}, \; i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; \tag{24}$$

Step 3. *Normalization No. 2.*

$$\widetilde{t}^{*}_{ij} = \frac{\widetilde{x}_{ij}}{\sqrt{\sum_{i=1}^{m} \widetilde{x}^{2}_{ij}}}; \; i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; \tag{25}$$

As it is generally known, in MCDM problems certain criteria should be minimized, also known as cost criteria, and the others should be maximized, often named as benefit criteria. The normalization procedure in Steps 2 and 3 should be applied for both criteria types (min and max).

Step 4. *Aggregated normalization.*

The aggregated normalization is obtained by Equation (25).

$$\widetilde{t}^{norm}_{ij} = \frac{\beta \widetilde{t}_{ij} + (1-\beta)\widetilde{t}^{*}_{ij}}{2}; \; i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; \tag{26}$$

where $\widetilde{t}^{norm}_{ij}$ denotes the aggregated averaged normalization. β is a weighting factor for each type of normalization varying from 0 to 1.

Step 5. *Weighted aggregated normalized decision-making matrix.*

In this step, the aggregated normalized decision-making (DM) matrix should be multiplied by the criteria weights to obtain a weighted DM matrix. Here, the weights of criteria are determined by the previously explained Fuller triangle method.

$$\hat{\tilde{t}}_{ij} = W_{ij} \cdot \tilde{t}_{ij}^{norm}\ ;\ i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; \tag{27}$$

Step 6. *Summation of weighted aggregated normalized DM per the criteria type.*

Further procedure relates to a summation of the normalized weighted values separately for the criteria type min ($\tilde{L}_i$) and the type max ($\tilde{A}_i$).

$$\tilde{L}_i \sum_{j=1}^{n} \widehat{\tilde{t}}_{ij}^{(min)}\ ;\ i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; \tag{28}$$

$$\tilde{A}_i \sum_{j=1}^{n} \widehat{\tilde{t}}_{ij}^{(max)}\ ;\ i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; \tag{29}$$

Step 7. *Raise the obtained $\tilde{L}_i$ and $\tilde{A}_i$ values to the degree of λ.*

$$\hat{\tilde{L}}_i = \tilde{L}_i^{\lambda} = \left(\sum_{j=1}^{n} \widehat{\tilde{t}}_{ij}^{(min)} \right)^{\lambda}\ ;\ i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; \tag{30}$$

$$\hat{\tilde{A}}_i = \tilde{A}_i^{1-\lambda} = \left(\sum_{j=1}^{n} \widehat{\tilde{t}}_{ij}^{(max)} \right)^{1-\lambda}\ ;\ i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; \tag{31}$$

where λ represents the coefficient degree of the criterion type. Parameter λ can be determined in different ways; however, we propose using the weights obtained by the Fuller triangle method. If we mark the weights of the criteria of min type by w_j^{min}, then the parameter λ can be obtained by Equation (31).

$$\lambda = \sum_{j=1}^{n} w_j^{min};\ j = 1, 2, \ldots, n \tag{32}$$

Step 8. *Calculate the final ranking.*

To obtain the final ranking of alternatives (R_i), the difference between the values $\hat{\tilde{A}}_i$ and $\hat{\tilde{L}}_i$ should be calculated and the final ranking equation applied.

$$R_i = e^{(\hat{\tilde{A}}_i - \hat{\tilde{L}}_i)};\ i = 1, 2, \ldots, m \tag{33}$$

4. Case Study

To demonstrate the applicability of the proposed methodology, we provide an illustrative numerical example. Let us suppose that the task to be solved is to select the most appropriate bus driver from the three candidates who applied for the job. The candidates can be considered the alternatives in the MCDM process, and we denote them as A1, A2, and A3. The criteria that are used for the evaluation of candidates are identified in the literature. According to the model, the number of criteria should be reduced to seven. This will be completed by interviewing the experts from the field and implementing the Fuller triangle method which gives the importance rank for each considered criterion. However, additional information about the criteria and their interdependence can be obtained by the DEMATEL method.

Since both the DEMATEL and the Fuller triangle method belong to the group of subjective methods, the first task in their implementation is to identify and interview the appropriate experts. In this case study, we collected the answers from three experts. The first is from the field of Traffic psychology and the other two are experts in Road traffic safety. All experts have more than 15 years of professional experience. They also possess Ph.D. degrees.

4.1. The Results of the DEMATEL Method

As explained in the methodology section, there are four steps in the DEMATEL implementation.

Step 1. *The experts assessed the interdependence between the criteria in the pair-wise comparisons and gave marks from 0 to 4 depending on the type of relation. Their answers are presented in Tables A1, A3 and A5 in Appendices A–C. Based on these answers, we formed the direct-relation matrix, as shown in Table 4.*

Table 4. The direct-relation matrix.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**
C1	0.00	1.33	1.00	0.00	1.00	0.00	0.67	1.00	0.67	0.67	0.67	1.33	0.67	0.67
C2	1.67	0.00	2.33	0.67	0.67	0.67	0.33	0.67	0.67	1.00	1.33	0.67	0.33	0.00
C3	0.67	0.67	0.00	0.33	1.00	0.67	0.00	0.00	0.00	0.00	0.00	1.00	0.67	0.00
C4	0.00	0.67	2.67	0.00	1.00	1.00	0.67	1.00	0.00	0.00	1.00	0.67	0.00	0.00
C5	1.00	1.33	2.33	0.67	0.00	0.00	0.33	1.67	0.67	0.67	2.33	1.00	0.67	0.00
C6	0.00	1.00	1.33	0.67	0.67	0.00	0.00	0.33	0.33	0.33	1.00	0.00	0.00	0.00
C7	0.67	0.67	0.33	0.67	0.67	0.00	0.00	1.67	1.00	0.67	1.67	1.00	0.00	0.00
C8	1.00	0.67	0.33	1.00	2.33	0.00	0.33	0.00	1.67	2.33	2.00	1.67	0.33	0.33
C9	0.67	0.67	0.00	0.00	1.00	0.67	0.67	1.67	0.00	2.67	0.67	0.00	0.00	0.67
C10	0.67	1.00	0.00	0.00	1.00	0.00	0.67	2.00	2.67	0.00	1.00	0.00	0.00	0.67
C11	0.67	0.67	1.00	1.00	1.67	0.67	0.00	1.67	0.67	0.67	0.00	1.00	0.67	0.67
C12	0.33	0.67	1.33	1.00	1.00	0.00	0.67	1.67	0.00	0.00	1.00	0.00	1.67	0.00
C13	0.67	0.67	0.67	0.00	1.00	0.00	0.00	0.67	0.00	0.00	1.00	1.33	0.00	0.00
C14	0.33	0.33	0.00	0.00	0.00	0.00	0.00	0.67	1.33	1.33	1.33	0.00	0.00	0.00

Step 2. *The normalized direct-relation matrix X is calculated according to Equations (2) and (3). The resulting matrix is in Table 5.*

Table 5. The normalized direct-relation matrix.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**
C1	0.00	0.10	0.07	0.00	0.07	0.00	0.05	0.07	0.05	0.05	0.05	0.10	0.05	0.05
C2	0.12	0.00	0.17	0.05	0.05	0.05	0.02	0.05	0.05	0.07	0.10	0.05	0.02	0.00
C3	0.05	0.05	0.00	0.02	0.07	0.05	0.00	0.00	0.00	0.00	0.00	0.07	0.05	0.00
C4	0.00	0.05	0.19	0.00	0.07	0.07	0.05	0.07	0.00	0.00	0.07	0.05	0.00	0.00
C5	0.07	0.10	0.17	0.05	0.00	0.00	0.02	0.12	0.05	0.05	0.17	0.07	0.05	0.00
C6	0.00	0.07	0.10	0.05	0.05	0.00	0.00	0.02	0.02	0.02	0.07	0.00	0.00	0.00
C7	0.05	0.05	0.02	0.05	0.05	0.00	0.00	0.12	0.07	0.05	0.12	0.07	0.00	0.00
C8	0.07	0.05	0.02	0.07	0.17	0.00	0.02	0.00	0.12	0.17	0.14	0.12	0.02	0.02
C9	0.05	0.05	0.00	0.00	0.07	0.05	0.05	0.12	0.00	0.19	0.05	0.00	0.00	0.05
C10	0.05	0.07	0.00	0.00	0.07	0.00	0.05	0.14	0.19	0.00	0.07	0.00	0.00	0.05
C11	0.05	0.05	0.07	0.07	0.12	0.05	0.00	0.12	0.05	0.05	0.00	0.07	0.05	0.05
C12	0.02	0.05	0.10	0.07	0.07	0.00	0.05	0.12	0.00	0.00	0.07	0.00	0.12	0.00
C13	0.05	0.05	0.05	0.00	0.07	0.00	0.00	0.05	0.00	0.00	0.07	0.10	0.00	0.00
C14	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.05	0.10	0.10	0.10	0.00	0.00	0.00

Step 3. *We calculated the total-relation matrix (Table 6) by using MATLAB software. It is applied also to create a causal diagram in the fourth step.*

Table 6. The total-relation matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
C1	0.11	0.21	0.22	0.08	0.23	0.04	0.10	0.24	0.16	0.18	0.22	0.22	0.12	0.09
C2	0.23	0.14	0.33	0.13	0.23	0.10	0.08	0.23	0.16	0.19	0.26	0.18	0.10	0.05
C3	0.10	0.11	0.09	0.06	0.15	0.07	0.03	0.08	0.05	0.05	0.09	0.13	0.09	0.02
C4	0.09	0.15	0.32	0.07	0.21	0.11	0.08	0.20	0.08	0.09	0.21	0.16	0.07	0.03
C5	0.21	0.25	0.36	0.15	0.23	0.07	0.09	0.33	0.19	0.21	0.37	0.24	0.15	0.05
C6	0.07	0.14	0.19	0.09	0.14	0.03	0.03	0.12	0.08	0.09	0.16	0.07	0.04	0.02
C7	0.16	0.17	0.18	0.13	0.22	0.05	0.06	0.30	0.19	0.19	0.29	0.20	0.08	0.05
C8	0.23	0.23	0.26	0.19	0.41	0.07	0.11	0.28	0.30	0.35	0.39	0.29	0.13	0.09
C9	0.16	0.18	0.15	0.08	0.24	0.09	0.11	0.30	0.16	0.33	0.23	0.12	0.06	0.10
C10	0.17	0.20	0.16	0.09	0.26	0.05	0.11	0.34	0.33	0.18	0.26	0.13	0.07	0.10
C11	0.17	0.19	0.25	0.16	0.30	0.10	0.06	0.30	0.18	0.19	0.20	0.21	0.13	0.09
C12	0.13	0.16	0.25	0.15	0.23	0.05	0.09	0.27	0.10	0.11	0.23	0.13	0.19	0.03
C13	0.12	0.13	0.16	0.06	0.18	0.03	0.03	0.16	0.07	0.08	0.18	0.18	0.06	0.02
C14	0.09	0.10	0.08	0.04	0.11	0.03	0.04	0.16	0.18	0.19	0.19	0.07	0.04	0.03

Step 4. *A causal diagram is formed based on D and R values calculated by Equations (6) and (7) and obtained values are in Table 7. Finally, a causal diagram is shown in Figure 5.*

Table 7. *D* and *R* values.

Criterion	*D* Values	*R* Values	$D + R$	$D - R$
C1	2.2332	2.0404	4.2736	0.1928
C2	2.3986	2.3421	4.7407	0.0565
C3	1.1113	3.0015	4.1129	−1.8902
C4	1.8706	1.4894	3.3600	0.3813
C5	2.8875	3.1333	6.0208	−0.2458
C6	1.2819	0.8855	2.1674	0.3964
C7	2.2486	1.0195	3.2681	1.2292
C8	3.3333	3.3073	6.6406	0.0259
C9	2.3082	2.2282	4.5364	0.0800
C10	2.4422	2.4269	4.8691	0.0153
C11	2.5329	3.2905	5.8234	−0.7577
C12	2.1374	2.3323	4.4697	−0.1949
C13	1.4515	1.3153	2.7668	0.1362
C14	1.3436	0.7686	2.1122	0.5750

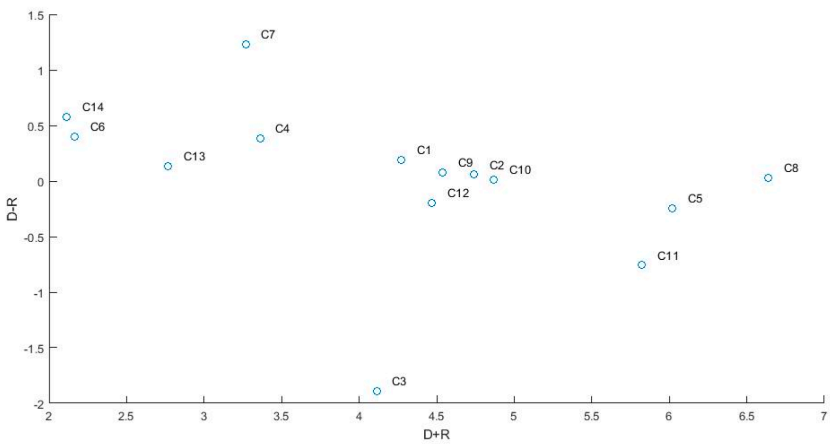

Figure 5. A causal diagram.

As can be noticed from Figure 5, criteria C3, C5, C11, and C12 belong to the effect group, while the others are in the cause group. Since we can conclude about a relatively low interdependence between the criteria, this is a good prerequisite to conducting the Fuller triangle method.

4.2. The Results of the Fuller Triangle Method

The procedure is carried out according to the previous methodological explanation.

Step 1. *We formed a triangular structure where 14 criteria were involved. Such a form was offered to the experts and they were asked to make pairwise comparisons of criteria in the case of the bus driver selection problem. Their answers are presented in Tables A2, A4 and A6 in Appendices A–C. The fields marked with green color are their choices.*
Step 2. *Further procedure implies counting the collected answers. In Table 8, Columns 3, 5, and 7, are the point that each criterion received by experts 1, 2, and 3, respectively.*
Step 3. *The relevance ranks (w_j) are calculated for each criterion and each expert and presented in Table 8, Columns 4, 6, and 8.*
Step 4. *The final relevance ranks are obtained. They are presented in the final column of Table 8, as well as in Figure 6, where they are aligned in descending order to easier notice the first seven that will be used in the further calculations.*

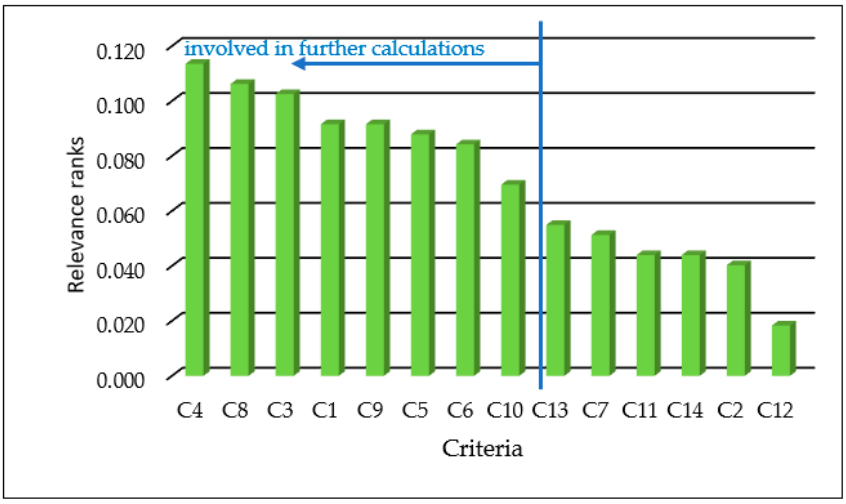

Figure 6. Descending order of the relevance ranks of criteria.

Table 8. The relevance ranks of criteria obtained by the Fuller triangle method.

No.	Criteria	Number of Preferences by Expert 1	w_j Based on Expert 1	Number of Preferences by Expert 2	w_j Based on Expert 2	Number of Preferences by Expert 3	w_j Based on Expert 3	Final w_j
1.	Attention	9	0.099	8	0.088	8	0.088	0.092
2.	Fatigue resistance	1	0.011	4	0.044	6	0.066	0.040
3.	Reaction time	9	0.099	9	0.099	10	0.110	0.103
4.	Visual abilities	10	0.110	10	0.110	11	0.121	0.114
5.	Speed estimation	8	0.088	8	0.088	8	0.088	0.088
6.	Physical fitness	8	0.088	7	0.077	8	0.088	0.084
7.	Driving experience	4	0.044	4	0.044	6	0.066	0.051
8.	Risk assessment	9	0.099	10	0.110	10	0.110	0.106
9.	Impulsiveness	9	0.099	8	0.088	8	0.088	0.092
10.	Aggressiveness	6	0.066	7	0.077	6	0.066	0.070
11.	Self-assessment of driving ability	6	0.066	4	0.044	2	0.022	0.044
12.	Space capabilities	2	0.022	2	0.022	1	0.011	0.018
13.	Intelligence	6	0.066	6	0.066	3	0.033	0.055
14.	Morality	4	0.044	4	0.044	4	0.044	0.044
	Total	91	1	91	1	91	1	1

To check the reliability of the obtained results, we interviewed the experts in the second round to collect information about the percentage distribution of criteria importance. The results are shown in Table 9. As it can be concluded, the rate of inconsistency is below 0.1 (RI = 0.07), which means that reliability is satisfactory.

Table 9. Calculation of the rate of inconsistency.

Criteria	w_j	Expert 1 [%]	Expert 2 [%]	Expert 3 [%]	Average Assessment—p_j	$\left\|w_{j*100} - p_j\right\|$	RI_j
C1	0.092	12	10	13	11.667	1.777	0.0178
C2	0.040	2	1	3	2.000	0.901	0.0090
C3	0.103	10	10	8	9.333	0.557	0.0056
C4	0.114	10	12	11	11.000	0.011	0.0001
C5	0.088	9	9	10	9.333	0.542	0.0054
C6	0.084	8	9	9	8.667	0.125	0.0012
C7	0.051	5	4	5	4.667	0.271	0.0027
C8	0.106	9	10	9	9.333	0.557	0.0056
C9	0.092	9	10	10	9.667	0.223	0.0022
C10	0.070	6	6	8	6.667	0.073	0.0007
C11	0.044	6	7	5	6.000	0.593	0.0059
C12	0.018	3	2	2	2.333	0.136	0.0014
C13	0.055	7	6	4	5.667	0.927	0.0093
C14	0.044	4	4	3	3.667	0.729	0.0073
							RI = 0.0742

4.3. The Results of a Hybridized Fuzzy–AROMAN–Fuller Approach

As we mentioned, the subject of the case study is a bus-operating company that needs to hire a bus driver. Three potential candidates are marked by A1, A2, and A3, the interviewed experts by E1, E2, and E3, and set evaluation criteria from C1 to C14, where only seven of them are considered in this part of the model. The structure of the considered MCDM problem is shown in Figure 7.

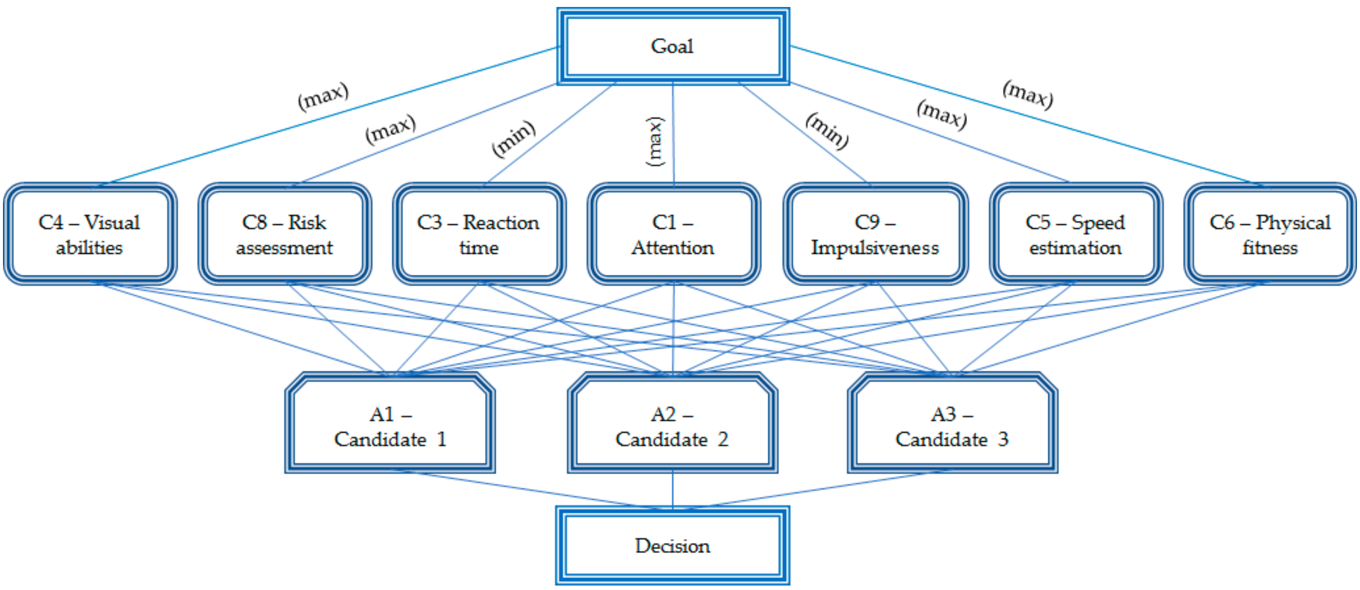

Figure 7. The structure of the MCDM problem.

The implementation of the Fuzzy–AROMAN–Fuller approach for solving the mentioned problem is presented in steps, as previously explained in the methodological section.

Step 1. *Let us suppose that the experts use linguistic variables to evaluate the alternatives and that their answers form the initial decision-making matrix as shown in Table 10. The linguistic inputs are converted to fuzzy numbers following the rules presented in Table 3. The fuzzy decision matrix that is averaged by Equation (23) is shown in Table 11.*

Table 10. The ratings of candidates.

Criteria	Candidates	Experts		
		E1	**E2**	**E3**
C4	A1	H	M	M
	A2	VH	H	H
	A3	H	H	MH
C8	A1	M	MH	M
	A2	MH	H	H
	A3	ML	M	M
C3	A1	H	MH	MH
	A2	L	VL	L
	A3	M	ML	ML
C1	A1	H	MH	M
	A2	M	H	H
	A3	VH	H	H
C9	A1	M	M	M
	A2	MH	M	M
	A3	H	MH	MH
C5	A1	MH	M	M
	A2	H	MH	H
	A3	VH	H	MH
C6	A1	M	ML	ML
	A2	M	H	MH
	A3	MH	M	MH

Table 11. The fuzzy decision matrix.

	C4	C8	C3	C1	C9	C5	C6
A1	(4.33, 6.33, 8)	(3.67, 5.67, 7.67)	(5.67, 7.67, 9.33)	(5, 7, 8.67)	(3, 5, 7)	(3.67, 5.67, 7.67)	(1.67, 3.67, 5.67)
A2	(7.67, 9.33, 10)	(6.33, 8.33, 9.67)	(0, 0.67, 2.33)	(5.67, 7.67, 9)	(3.67, 5.67, 7.67)	(6.33, 8.33, 9.67)	(5, 7, 8.67)
A3	(6.33, 8.33, 9.67)	(2.33, 4.33, 6.33)	(1.67, 3.67, 5.67)	(7.67, 9.33, 10)	(5.67, 7.67, 9.33)	(7, 8.67, 9.67)	(4.33, 6.33, 8.33)

Step 2. *Normalization No. 1 is performed and the obtained results are shown in Table 12.*

Table 12. Normalization No. 1 of the fuzzy decision matrix.

	C4	C8	C3	C1	C9	C5	C6
A1	(0, 0.35, 0.65)	(0.18, 0.45, 0.73)	(0.61, 0.82, 1)	(0, 0.4, 0.73)	(0, 0.32, 0.63)	(0, 0.33, 0.67)	(0, 0.28, 0.57)
A2	(0.59, 0.88, 1)	(0.54, 0.82, 1)	(0, 0.07, 0.25)	(0.13, 0.53, 0.8)	(0.11, 0.42, 0.74)	(0.44, 0.78, 1)	(0.48, 0.76, 1)
A3	(0.35, 0.71, 0.94)	(0, 0.27, 0.55)	(0.18, 0.39, 0.61)	(0.53, 0.87, 1)	(0.42, 0.74, 1)	(0.56, 0.83, 1)	(0.38, 0.67, 0.95)

Step 3. *Normalization No. 2 is complete and the obtained results are in Table 13.*

Table 13. Normalization No. 2 of the fuzzy decision matrix.

	C4	C8	C3	C1	C9	C5	C6
A1	(0.27, 0.45, 0.74)	(0.26, 0.52, 0.99)	(0.51, 0.90, 1.58)	(0.31, 0.50, 0.81)	(0.21, 0.46, 0.95)	(0.23, 0.43, 0.76)	(0.13, 0.36, 0.83)
A2	(0.48, 0.67, 0.92)	(0.45, 0.76, 1.26)	(0, 0.08, 0.39)	(0.35, 0.55, 0.84)	(0.26, 0.53, 1.04)	(0.40, 0.63, 0.95)	(0.38, 0.69, 1.27)
A3	(0.39, 0.59, 0.89)	(0.17, 0.39, 0.82)	(0.14, 0.43, 0.96)	(0.48, 0.67, 0.93)	(0.41, 0.71, 1.26)	(0.47, 0.65, 0.95)	(0.32, 0.63, 1.22)

Step 4. *The aggregated normalization is calculated by Equation (26), where we considered the parameter β to be 0.5. The results are in Table 14.*

Table 14. Aggregated normalization of the fuzzy decision matrix.

	C4	C8	C3	C1	C9	C5	C6
A1	(0.14, 0.40, 0.69)	(0.22, 0.49, 0.86)	(0.55, 0.86, 1.29)	(0.16, 0.45, 0.77)	(0.21, 0.46, 0.95)	(0.12, 0.38, 0.71)	(0.06, 0.32, 0.70)
A2	(0.53, 0.77, 0.96)	(0.50, 0.79, 1.13)	(0, 0.07, 0.32)	(0.24, 0.54, 0.82)	(0.26, 0.53, 1.04)	(0.42, 0.70, 0.98)	(0.43, 0.73, 1.14)
A3	(0.37, 0.65, 0.92)	(0.08, 0.33, 0.68)	(0.16, 0.41, 0.78)	(0.51, 0.77, 0.96)	(0.41, 0.71, 1.26)	(0.50, 0.74, 0.98)	(0.35, 0.65, 1.09)

Step 5. *Next, the weighted fuzzy decision-making matrix is formed. We used the weights obtained by the Fuller triangle method; however, since the number of criteria is reduced from 14 to 7, we arranged the sum of the remaining 7 weights to be equal to 1. The resulting weighted matrix is shown in Table 15.*

Table 15. The weighted fuzzy decision matrix.

	C4	C8	C3	C1	C9	C5	C6
A1	(0.02, 0.07, 0.12)	(0.03, 0.08, 0.14)	(0.08, 0.13, 0.20)	(0.02, 0.06, 0.10)	(0.01, 0.05, 0.10)	(0.02, 0.05, 0.09)	(0.01, 0.04, 0.09)
A2	(0.09, 0.13, 0.16)	(0.08, 0.12, 0.18)	(0, 0.01, 0.05)	(0.03, 0.07, 0.11)	(0.02, 0.06, 0.12)	(0.06, 0.09, 0.13)	(0.05, 0.09, 0.14)
A3	(0.06, 0.11, 0.15)	(0.01, 0.05, 0.11)	(0.02, 0.06, 0.12)	(0.07, 0.10, 0.13)	(0.06, 0.10, 0.15)	(0.06, 0.10, 0.13)	(0.04, 0.08, 0.13)

Step 6. *In this step, the summation of the weighted aggregated normalized fuzzy decision-making matrix should be completed per the criteria type. In our case, the min type criteria are C3 and C9, while the max type criteria are C4, C8, C1, C5, and C6.*
Step 7. *The sums from Step 6 should be raised to the degree of λ, which is in our case, according to Equation (32) equal to 0.29. The obtained values are in Table 16.*

Table 16. Summation of weighted fuzzy decision matrix per the criteria type.

	$\hat{\tilde{L}}_i$	$\hat{\tilde{A}}_i$
A1	(0.52, 0.61, 0.71)	(0.20, 0.42, 0.64)
A2	(0.35, 0.48, 0.60)	(0.43, 0.62, 0.79)
A3	(0.49, 0.59, 0.69)	(0.38, 0.56, 0.74)

Step 8. *In the final step, we calculate the final ranking by Equation (33). As shown in Table 17, the results of implemented method indicate that the best candidate is A2, followed by A3 and A1.*

Table 17. Final ranking.

	R_i
A1	0.82
A2	1.15
A3	0.97

5. Conclusions

The problem of personnel selection is very complex, bearing in mind that multiple criteria should be considered in the candidate evaluation process. The task is even more complicated when it comes to demanding jobs, such is the job of a professional driver. There is often a need to manipulate uncertain or imprecise data. In this paper, we demonstrated how a hybridized Fuzzy–AROMAN–Fuller approach can be successfully used to solve the considered problem.

This research resulted in several contributions. First of all, by reviewing the literature from the field of traffic psychology, road safety, and personnel selection, we identified the criteria that should be used in the process of professional driver selection. Further, we interviewed the experts to determine the relevance ranks of the set criteria. We interviewed three eminent experts from the field of road traffic safety and traffic psychology; however, a direction for future research can be to include more experts in the research and to compare the results. Finally, for the first time in the literature, we applied the AROMAN method in a fuzzy environment. We further couple it with the Fuller triangle method. By solving a numerical example, we demonstrated the applicability of the proposed model. Additional paths for future research can be directed toward comparing the obtained results with some other MCDM approaches. For example, the criteria weights can be determined by AHP and coupled with the AROMAN method, or the final ranking of alternatives can be performed by some other MCDM method and be compared with the AROMAN.

Although we demonstrated the proposed model on the example of a professional driver selection problem, this model is general and can be applied to many other problems. These problems can relate to personnel selection in other fields; however, a hybridized Fuzzy–AROMAN–Fuller approach can be implemented for solving any other MCDM problem.

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Appendix A. Answers from Expert 1

Table A1. Answers related to the DEMATEL method from Expert 1.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
C1	0	2	1	0	1	0	1	1	1	1	1	1	1	1
C2	2	0	2	1	1	1	1	1	1	1	2	1	1	0
C3	1	1	0	1	1	1	0	0	0	0	0	1	1	0
C4	0	1	3	0	1	1	1	1	0	0	1	1	0	0
C5	1	1	2	1	0	0	1	2	1	1	2	1	0	0
C6	0	1	1	1	0	0	0	0	0	0	1	0	0	0
C7	0	1	0	1	2	0	0	2	1	1	2	1	0	0
C8	1	1	0	1	2	0	1	0	2	2	2	2	1	1
C9	1	1	0	0	1	2	1	2	0	3	1	0	0	1
C10	1	1	0	0	1	0	1	2	3	0	1	0	0	1
C11	1	0	1	1	2	1	0	2	1	1	0	1	1	1
C12	1	1	1	1	1	0	1	2	0	0	1	0	2	0
C13	1	1	1	0	1	0	0	1	0	0	1	2	0	0
C14	0	0	0	0	0	0	0	1	1	1	1	0	0	0

Table A2. Answers related to the Fuller triangle method from Expert 1.

C1	**C1**	C1	C1	**C1**	**C1**	C1	**C1**	**C1**	**C1**	**C1**	**C1**	**C1**
C2	C3	**C4**	**C5**	C6	C7	**C8**	C9	C10	C11	C12	C13	C14
C2	C2	C2	C2	C2	C2	C2	C2	C2	C2	C2	C2	
C3	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**	
C3	**C3**	**C3**	C3	**C3**	**C3**	**C3**	**C3**	**C3**	C3	**C3**		
C4	C5	C6	**C7**	C8	C9	C10	C11	C12	**C13**	C14		
C4	C4	**C4**	C4	**C4**	**C4**	**C4**	**C4**	**C4**	**C4**			
C5	**C6**	C7	**C8**	C9	C10	C11	C12	C13	C14			
C5	**C5**	C5	C5	C5	**C5**	**C5**	**C5**	**C5**				
C6	C7	**C8**	**C9**	**C10**	C11	C12	C13	C14				
C6	C6	C6	**C6**	**C6**	**C6**	**C6**	**C6**					
C7	**C8**	**C9**	C10	C11	C12	C13	C14					
C7	C7	C7	C7	C7	C7	**C7**						
C8	**C9**	**C10**	**C11**	**C12**	**C13**	C14						
C8	**C8**	C8	**C8**	C8	**C8**							
C9	C10	**C11**	C12	**C13**	C14							
C9	C9	**C9**	**C9**	**C9**								
C10	**C11**	C12	C13	C14								
C10	**C10**	**C10**	C10									
C11	C12	C13	**C14**									
C11	**C11**	C11										
C12	C13	**C14**										
C12	C12											
C13	**C14**											
C13												
C14												

The green color indicates the answer of the expert, i.e., which criterion is more important in a pair-wise comparison.

Appendix B. Answers from Expert 2

Table A3. Answers related to the DEMATEL method from Expert 2.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**
C1	0	1	1	0	1	0	0	1	0	0	0	2	0	0
C2	1	0	2	1	1	0	0	1	1	1	0	0	0	0
C3	0	0	0	0	1	0	0	0	0	0	0	1	1	0
C4	0	0	2	0	1	1	1	1	0	0	1	0	0	0
C5	1	2	3	0	0	0	0	2	1	1	3	1	1	0
C6	0	1	1	0	1	0	0	0	1	1	1	0	0	0
C7	1	0	0	1	0	0	0	2	1	0	1	1	0	0
C8	1	0	1	1	3	0	0	0	2	2	2	2	0	0
C9	0	0	0	0	1	0	0	1	0	4	0	0	0	1
C10	0	1	0	0	1	0	0	2	4	0	1	0	0	1
C11	0	1	1	1	2	1	0	2	1	1	0	1	1	1
C12	0	1	1	1	1	0	1	2	0	0	1	0	2	0
C13	1	1	0	0	1	0	0	1	0	0	1	2	0	0
C14	0	0	0	0	0	0	0	0	1	1	1	0	0	0

Table A4. Answers related to the Fuller triangle method from Expert 2.

C1	C1	C1	**C1**	C1	**C1**	C1	**C1**	**C1**	**C1**	**C1**	C1	**C1**
C2	**C3**	**C4**	C5	**C6**	C7	**C8**	C9	C10	C11	C12	**C13**	C14
C2	C2	C2	**C2**	**C2**	C2	**C2**	C2	C2	C2	C2	C2	
C3	**C4**	**C5**	C6	C7	**C8**	C9	**C10**	**C11**	**C12**	**C13**	**C14**	
C3	**C3**	**C3**	**C3**	C3	C3	**C3**	**C3**	**C3**	**C3**	**C3**		
C4	C5	C6	C7	**C8**	**C9**	C10	C11	C12	C13	C14		
C4	C4	C4	**C4**	**C4**	**C4**	**C4**	**C4**	**C4**	**C4**			
C5	**C6**	**C7**	C8	C9	C10	C11	C12	C13	C14			
C5	**C5**	C5	C5	C5	**C5**	**C5**	**C5**	**C5**				
C6	C7	**C8**	**C9**	**C10**	C11	C12	C13	C14				
C6	**C6**	C6	**C6**	C6	**C6**	**C6**	C6					
C7	C8	**C9**	C10	**C11**	C12	C13	**C14**					
C7	C7	C7	**C7**	C7	C7	**C7**						
C8	**C9**	**C10**	C11	**C12**	**C13**	C14						
C8	**C8**	**C8**	**C8**	**C8**	**C8**							
C9	C10	C11	C12	C13	C14							
C9	**C9**	**C9**	**C9**	**C9**								
C10	C11	C12	C13	C14								
C10	**C10**	C10	**C10**									
C11	C12	**C13**	C14									
C11	C11	**C11**										
C12	**C13**	C14										
C12	C12											
C13	**C14**											
C13												
C14												

The green color indicates the answer of the expert, i.e. which criterion is more important in a pair-wise comparison.

Appendix C. Answers from Expert 3

Table A5. Answers related to the DEMATEL method from Expert 3.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**
C1	0	1	1	0	1	0	1	1	1	1	1	1	1	1
C2	2	0	3	0	0	1	0	0	0	1	2	1	0	0
C3	1	1	0	0	1	1	0	0	0	0	0	1	0	0
C4	0	1	3	0	1	1	0	1	0	0	1	1	0	0
C5	1	1	2	1	0	0	0	1	0	0	2	1	1	0
C6	0	1	2	1	1	0	0	1	0	0	1	0	0	0
C7	1	1	1	0	0	0	0	1	1	1	2	1	0	0
C8	1	1	0	1	2	0	0	0	1	3	2	1	0	0
C9	1	1	0	0	1	0	1	2	0	1	1	0	0	0
C10	1	1	0	0	1	0	1	2	1	0	1	0	0	0
C11	1	1	1	1	1	0	0	1	0	0	0	1	0	0
C12	0	0	2	1	1	0	0	1	0	0	1	0	1	0
C13	0	0	1	0	1	0	0	0	0	0	1	0	0	0
C14	1	1	0	0	0	0	0	1	2	2	2	0	0	0

Table A6. Answers related to the Fuller triangle method from Expert 3.

C1	C1	C1	C1	C1	C1	C1	C1	C1	C1	C1	C1	C1
C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
C2	C2	C2	C2	C2	C2	C2	C2	C2	C2	C2	C2	
C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	
C3	C3	C3	C3	C3	C3	C3	C3	C3	C3	C3		
C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14		
C4	C4	C4	C4	C4	C4	C4	C4	C4	C4			
C5	C6	C7	C8	C9	C10	C11	C12	C13	C14			
C5	C5	C5	C5	C5	C5	C5	C5	C5				
C6	C7	C8	C9	C10	C11	C12	C13	C14				
C6	C6	C6	C6	C6	C6	C6	C6					
C7	C8	C9	C10	C11	C12	C13	C14					
C7	C7	C7	C7	C7	C7	C7						
C8	C9	C10	C11	C12	C13	C14						
C8	C8	C8	C8	C8	C8							
C9	C10	C11	C12	C13	C14							
C9	C9	C9	C9	C9								
C10	C11	C12	C13	C14								
C10	C10	C10	C10									
C11	C12	C13	C14									
C11	C11	C11										
C12	C13	C14										
C12	C12											
C13	C14											
C13												
C14												

The green color indicates the answer of the expert, i.e. which criterion is more important in a pair-wise comparison.

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