symmetry

MDPI

Article

Synergies of Text Mining and Multiple Attribute Decision Making: A Criteria Selection and Weighting System in a Prospective MADM Outline

Sarfaraz Hashemkhani Zolfani * and Arman Derakhti

School of Engineering, Catholic University of the North, Larrondo 1281, Coquimbo 1780000, Chile; derakhti.arman@ucn.cl
* Correspondence: sarfaraz.hashemkhani@ucn.cl

Received: 21 April 2020; Accepted: 19 May 2020; Published: 25 May 2020

check for updates

Abstract: In this study, a new way of criteria selection and a weighting system will be presented in a multi-disciplinary framework. Weighting criteria in Multi-Attribute Decision Making (MADM) has been developing as the most attractive section in the field. Although many ideas have been developed during the last decades, there is no such great diversity that can be mentioned in the literature. This study is looking from outside the box and is presenting something totally new by using big data and text mining in a Prospective MADM outline. PMADM is a hybrid interconnected concept between the Futures Studies and MADM fields. Text mining, which is known as a useful tool in Futures Studies, is applied to create a widespread pilot system for weighting and criteria selection in the PMADM outline. Latent Semantic Analysis (LSA), as an influential method inside the general concept of text mining, is applied to show how a data warehouse's output, which in this case is Scopus, can reach the final criteria selection and weighting of the criteria.

Keywords: text mining; Multi-Attribute Decision Making (MADM), criteria selection; weighting; Prospective MADM; Latent Semantic Analysis (LSA)

---

1. Definition of the Current Study in the MADM Outline

Multiple Criteria Decision Making (MCDM) is a multidisciplinary area and field that is working actively in interdisciplinary atmospheres of such fields like management science, operations research and decision science [1,2]. MCDM has two separated parts, which are Multi-Attribute Decision Making (MADM) and Multi-Objective Decision Making (MODM), and it can be described shortly as follows: MADM problems can be considered as discrete problems and MODM problems as continuous problems [3,4]. The MADM structure is linked to the theory of Rational Choice, which is acting rationally with given information, constraints and conditions. Decisions can be made based on alternatives, criteria and the relative importance of them. On the other hand, the MODM framework is designed for non-predetermined alternatives, in which decision makers are involved in to find one of a set of appropriate answers for their models. Generally, the number of alternatives for a MODM problem is infinite [5,6].

At the present time, MADM models and methods are reflected and applied for decision-making problems in different majors and fields, which is not limited to the any special area or structure [7–13]. In the next section, all MADM methods will be introduced in Table 1. The main point about all common MADM methods is they can be categorized in certain sections that are usually predictable. It means all new contributions could be classified in common sections, which can be comparable as well. The four main contributions as categories are as follows:

Category 1:

Concentrate on criteria and their analysis and weighting, such as AHP [14], ANP [15,16], SWARA [17], Extended SWARA [18], FARE [19], BWM [20] and FUCOM [21]. The newest methods are BWM and FUCOM, and this part still has enough motivation from researchers to be worked on. Except for SWARA, they can evaluate alternatives but the key point about them is the analyzing of criteria.

Category 2:

Concentrate on analyzing for prioritizing and ranking of the alternatives that is really active these days. In comparison to the previous section, so many new methods (later than 2010) have been introduced lately, such as ARAS [22], WASPAS [23], EDAS [24], CODAS [2], CoCoSo [25] and MARCOS [26]. There is a trend, and we predict more and more methods will be introduced.

Category 3:

Hybrid new models that is really common and it can be mentioned, such as SWARA–COPRAS [27], SWARA–WASPAS [28], SWARA–VIKOR [29], SWARA–EDAS [30], BWM–WASPAS [31], BWM–MAIRCA [32], etc. With a new method, so many hybrid models can be developed, and this is a really common trend among researchers. This combination is imaginable between the two previous sections, in which one method applies for weighting criteria and another one for the evaluating and prioritizing of criteria.

Category 4:

The main aim is a comparison between methods with the basic and same logic, like VIKOR and TOPSIS [33], EDAS and TOPSIS [34] and SWARA and BWM [35], etc.

Category 5:

The combination of logics with MADM methods, such as fuzzy and grey, is another trend that is so common among researchers and it is the most active part of studies, somehow. It is so common to find different combinations of methods with the same logic but different details, such as interval type-2 fuzzy WASPAS and TOPSIS [36], Fuzzy BWM [37], Fuzzy EDAS, Fuzzy SWARA and Fuzzy CRITIC [38], Fuzzy ANP, Fuzzy TOPSIS and Fuzzy VIKOR [39], Fuzzy AHP and Fuzzy MAIRCA [40], Grey COPRAS and Fuzzy COPRAS [41], Fuzzy FUCOM [42] and Fuzzy group BWM–MULTIMOORA [43].

Table 1. Primary model of Prospective Multi-Attribute Decision Making (PMADM) based on limiters and boosters [44].

		C_1		C_{n+1}		C_n
Weights						
Limiters (L) /Boosters (B)		L_{1-1}... L_{1-n}		L_{n+1-1}... L_{n+1-n}		L_{n-1}... L_{n-n}
	Based on C_1	**Average**	**Based on C_{n+1}**	**Average**	**Based on C_n**	**Average**
A_1 without L						
A_1 based on $L_{1\text{-}1}$						
A_1 based on …						
A_1 based on $L_{1\text{-}n}$						
A_{n+1} without L						
A_{n+1} based on $L_{n+1\text{-}1}$						
A_{n+1} based on …						
A_{n+1} based on $L_{n+1\text{-}n}$						
A_n without L						
A_n based on $L_{n\text{-}1}$						
A_n based on …						
A_n based on $L_{n\text{-}n}$						

The main idea of the current study is to present a new way to weigh criteria based on something more scientific. Although using experts' opinions have had a great position in the decision-making history, results would not necessarily be accurate and robust [18]. Furthermore, one step backward is the criteria selection strategies usually conducted by researchers based on limited previous studies.

Criteria selection, itself, can be an essential part of defining an MADM model and MADM problem in reality. Accordingly, this study can be classified as in Section 1, and even as something newer that has not yet been added as a category of innovation in the MADM field. Text mining and its analysis can be a really powerful tool for finding the most critical criteria based on the entire data base, and then weighting the criteria based on the majority of existing reports and analysis of similar studies.

2. Definition of the Current Study in the Prospective MADM Outline

PMADM is a new approach and model for decision-making about the future in practice. Since introducing this new approach, a new sub-branch has been imaginable in the MADM framework, which can be developed more and more in reality. As can be analyzed from the literature of the MADM framework, some studies have been working since 1988 about the MADM structure and its framework in decision-making for future matters and topics [45–56]. Time (time period) consideration has been developed in decision-making problems and Dynamic MADM with different definitions could be considered as the last contribution regarding time consideration in MADM models.

The MADM and classic methods used to consider a decision in a stable and fixed state that could not be flexibly measured. Dynamic MADM (DMADM) has developed since around one decade ago but could not meet and support all necessities, needs and requirements. By developing "Futures Studies" and "Foresight" perspectives, imaginations and thoughts about the decision process about the future have changed. Classic decision-making structures could not meet such ideas like explorative and descriptive perspectives, so new paradigms and ideas have shaped since then. PMADM was introduced to cover and support all new aspects of needs and necessities of decision making about the future with a flexible idea.

PMADM as a new sub-branch in the MADM field, which is also a multidisciplinary area, and it can be considered as an approach in "Futures Studies" as well. PMADM is not limited to the classic dimensions of MADM and it can be developed in a really new space. Due to needs, new items can be added to the classic model and make that more applicable with more reliable and accurate outputs and decisions. In the first step, Limiters (L) and Boosters (B) are presented [44]. Limiters and Boosters as new items that will be considered in cases in which different scenarios can happen with different possibilities. Mostly it considers alternatives that will have a different quality in different scenarios. Hashemkhani Zolfani et al. [57,58] discussed the importance of considering the future in MADM models. Another new model has discussed about MADM framework and future scenarios in different states and situations [59].

PMADM has this potential to be developed in both concept and for introducing new methods that have the same framework. New items and rules can be added and considered in evaluating criteria and their weights, alternatives and the general concept. New methods with the basic structure of PMADM also can be developed for application in the future in a better way in real-world cases. Here, the main point is methods can be developed the same, original PMADM structure.

All the latest contributions of Prospective MADM are based on new items:

- Limiters/Boosters:

Hashemkhani Zolfani et al. [57] released the first contribution and definition of the PMADM outline, which can be explained as Limiters/Boosters. Limiters/Boosters can have the role of pay-offs of future scenarios for the evaluated alternatives in their positions. This fact can be demonstrated by examining where they are located in the structure of a classic MADM structure; for example, as shown in Table 1. Limiters and Boosters can be outputs of some future scenarios or just some future possibilities and can have a direct influence on the alternatives' analysis and expectations.

- Multi-Aspect Criterion

Multi-Aspect Criterion is a new item in the classic structure of MADM in the PMADM area. It contains two main shapes: "Hybrid criteria as a new criterion" and "a lately defined concept for the other criteria as a criterion". The importance of time will be showed with this new item to control the definitions during the period of time. In future definitions, criteria can be mixed or developed in different aspects and approaches. It is really important to have an explicit definition about a certain time in the future while the decision-making process is happening [60].

- Supportive-backup criteria

"Supportive-backup criteria" is another additive item to the PMADM outline. While different future scenarios are considered, this new item can be really useful. It shapes all future decision-making matrices into one matrix that decision-makers can shape to whatever they want and make their decisions better and more effective [61]. For instance, an example is illustrated in Table 2. "Supportive-backup criteria" gives great possibility to the researchers to consider a set of different future-possible scenarios for their calculations and evaluations. Decision-makers can have a back-up system for possible ways of managing and leading probable future scenarios in their decision models in advance.

Table 2. Position of the "Supportive-backup criteria" [61].

	$\mathbf{C_1}$	$\mathbf{C_2}$	$\mathbf{C_{n\text{-}1}}$	$\mathbf{C_n}$
Supportive/Backup Criteria	$\mathbf{C_{s1-1}}$	$\mathbf{C_{2*-s1}}$	$\mathbf{C_{s1-n-1-sb1}}$	…
	$\mathbf{C_{s2-1}}$	$\mathbf{C_{s1-2}}$	$\mathbf{C_{n-1*-s2}}$	…
	$\mathbf{C_{u1\text{-}1}}$	…	…	…
$\mathbf{A_1}$	**…**	…	…	…
Reserved A_1	…	…	…	…
Reserved A_1	…	…	…	…
Reserved A_1	…	…	…	…
…	…	…	…	…
…	…	…	…	…
…	…	…	…	…
A_n	…	…	…	…

- Sensitivity analysis of the experts based on Causal Layered Analysis (CLA)

Applying CLA as a qualitative "Futures Studies" field can give a great opportunity to the researchers of the MCDM field to evaluate many things, including analysis of experts who are going to be invited as a part of panel teams. This study showed how experts can be finally selected for cooperation in a study [62].

3. Research Gap and Case Study: "Machine Tool Selection"

Text mining has been accepted as a powerful and useful tool in foresight exercises [63]. Saritas & Burmaoglu [64] presented Text Mining as a method or tool in the field of Futures Studies, which includes Foresight as well. Prospective MADM is the output and interconnection of two multidisciplinary fields, namely Futures Studies and Multiple Criteria Decision Making. As a matter of fact, this research has a connection between three fields of study and can develop more possibilities for doing better studies in the future.

Making a critical decision for the future is so challenging and all the procedures can be really vital. Similar to the Multi-Aspect criterion, the procedure of defining criteria is a big challenge; therefore, reliability of selecting the most important criteria should be the core of an MADM problem and challenge. If researchers cannot define the best set of criteria, a logical, useful output would be out of reach.

Text Mining can help researchers to use big data to find the most important criteria and relative importance of each of them. The common way of defining a set of criteria in the MADM field is only a limited study field, and in a related literature review, a maximum of some interviews with limited accessible experts are available. Indeed, in numerous studies there is no need to use some older MADM methods (Category 1) for weighting criteria if we are working on future-based decisions in a big level of the study.

Machine tool selection has always been an important issue for decision-makers in different industries in order to make the most efficient and effective decisions. Over the past decades, many researchers studied, with various methodologies, which MCDM is the most well-known methodology that has been used several times. In all the past articles, the criteria and methodologies were selected based on the author's opinion; however, in this investigation we would like to implement a new way in order to classify the most relevant studies and the most significant themes. More specifically, we try to answer the following question: What are the main criteria and topics of current machine tool selection research?

To answer this question, the literature items or literature positions were analyzed by Latent Semantic Analysis (LSA), which revealed five important criteria on machine tool selection: size and precision, cost and serviceability, flexibility, productivity as well as technical features and safety. This study contributes to the machine tool selection literature by providing a comprehensive review of current machine tool selection studies and recognizing its primary research topics, which provides guideline for future studies. This new approach is a unique way to gather data and determine criteria by using text mining based on previous studies and this study would be able to serve as a research map for future MCDM articles.

4. Method

4.1. Data Collection

In order to attain all the related articles in the machine tool selection research landscape and identify the research area, we first searched for the "machine selection" and "MCDM" phrases—for all peer-reviewed academic publications—in their titles, abstract or author-supplied keywords in the SCOPUS database. This database presents the largest abstract and citation of peer-reviewed literature in scientific, technical, medical and social sciences. This process resulted in 107 articles, which means 107 publications exactly used the terms "machine selection" and "MCDM" in their titles, abstract or keywords. Then, the authors read all 107 publications in order to find out the most relevant studies. After reading all 107 abstracts, 28 publications were chosen to be considered as machine tool selection by the MCDM technique research. These 28 articles explain how to select the best machine tool by different MCDM techniques, in which most of the authors used hybrid techniques in order to find the best choice. The abstracts of these articles turned into a new raw data set for analyzing in Latent Semantic Analysis.

4.2. Data Analysis

With help of RapidMiner [65] a text mining approach was implemented that is a part of data mining tools. Distinct techniques form the text mining structure, such as natural language processing (NLP), machine learning, information extraction, information retrieval and statistics. This idea derives from "the machine supported analysis of text" [66]. Since this era is famous for data science, there have been many studies that investigated the use of text mining in the literature [67,68]. Latent Semantic Analysis is used in this study to extract the most significant and relevant criteria from the previous studies, which was implemented in different contributions [69,70]. In comparison to other text mining techniques that are only able to analyze textual data and count the occurrences of particular words, LSA can extract the contextual-usage meaning of words and estimates of similarities among words with the information at the semantic level [71]. Thus, the intuitive application of LSA has been growing in different sorts of text mining classifications, containing library indexing, search engine and natural language processing, and so on [72].

This study follows the text mining procedures that was used in previous studies [67,68,71,72]. The following steps explain all processes of the LSA, from the pre-processing term reduction and term frequency matrix transformation to the singular value decomposition.

First, we consider all abstracts as input data in this text mining technique; however, it did not work out very well because usually abstracts do not contain criteria and mostly discuss methodologies and their achievements. Therefore, we read all 28 publications in order to pull out the specific part that has the criteria in its context and then consolidated it in a spreadsheet, finally loading it into RapidMiner. It might form a doubt why we did not consider all parts of the publication as our input data: all the sections of an academic publication together may contain many different contexts and ideas, such as methodologies, literature, mathematic formulas, etc. Thus, we thought it would not a good decision to consider each article completely.

4.2.1. Pre-Processing and Term Reduction

In the first step, every record (the specific part pulled out of the publications) in the dataset is defined as a unique document. This function lets authors trace the results of the LSA back to a specific article to find out which one is of more significance. Secondly, in RapidMiner, the data were imported and called to the procedure by the retrieve operator. Each record was converted into a document object before it could be analyzed. Next, all the words were recognized as tokens and each token was diagnosed by space or a non-letter separator. Then, all tokens were transformed into the lower case, because it is essential to integrate all tokens in a unit format. For instance, "Machine Tool Selection" was considered to "machine tool selection". After that, the "stopwords English" operator removed all stopwords, such as "the", "is", "and", "a", "an", etc., in the English language. The presence of these stopwords do not make any valuable meaning and increases dimensionality. Afterwards, all the tokens that were less than two letters or more than twenty-five letters were removed because in none of both situations the tokens do not make sense. Then, the "stem porter" operator, which is one of the stemming techniques, was applied in order to decrease the number of words that has the same root. For example, "contribute", "contribution", "contributed" and "contributions" were considered as a single token, the "contribut". With the stemming process, plenty of similar words were decreased and this issue helps the dimensionality from a further increment. The result of these processes was concluded at 224 tokens. In this step, we realized that there are some common academic words that are used in academic publications. In order to eliminate these common academic tokens, we searched and selected an academic phrase bank [73]. This academic phrase bank specifically discusses phrases that are used in academic publications. In this step, we considered this book as a discrete input in another procedure and implemented the previous steps containing the tokenization, transforming to lower case, filtering English stopwords, filtering tokens by length and stemming, from where we took the result of 1907 tokens to a new dictionary in order to eliminate all the common academic words in the main process. After this reduction, the number of tokens decreased to 101.

4.2.2. Term Frequency Matrix Transformation

In this study, the technique of calculating the relatively rare weighting called Term Frequency-Inverse Document Frequency (TF-IDF) is used. The TF-IDF technique is a new approach of term frequency matrix transformation and is a fundamental procedure in different types of text mining techniques [68]. Such transformation promotes the occurrence of rare terms and decreases the impact of more common non-stopwords. TF-IDF is separated in two parts: first, TF explains the ratio of the number of times a keyword emerges in a given document, n_k (where k is keyword), to the total number of terms in the document, n:

$$TF = n_k/n$$

and IDF is defined as follows:

$$IDF = log_2\ (N/N_k)$$

where N is the number of documents and N_k is the number of documents that contain the keyword, K [74]. Then, TF-IDF is illustrated as follows:

$$TF\text{-}IDF = (n_k/n) * log_2\ (N/N_k)$$

4.2.3. Singular Value Decomposition (SVD)

Singular Value Decomposition (SVD) plays the most important role in the latent semantic analysis. SVD is a linear algebra technique, which is a factorization of a complex matrix. More information about computation of the SVD is presented in previous literature [75,76]. The major idea is to make a rectangular matrix A be broken down into the product of three matrices, an orthogonal matrix U, a diagonal matrix S and the transpose of an orthogonal matrix V, as follows:

$$A_{mn} = U_{mm} S_{mn} V^T{}_{nn}$$

where $U^T U = I$; $V^T V = I$; the columns of V are orthonormal eigen-vectors of $A^T A$; the columns of U are orthonormal eigenvectors of AA^T; and S is a diagonal m × n matrix containing the square roots of the eigenvalues from V or U in descending order. These eigenvalues indicate the variance of the linearly independent components along each dimension (factor).

Singular value decomposition gets the TF-IDF weighted term matrix and converts it into three matrices containing the term-by-factor matrix, document-by-factor matrix and singular value matrix (square roots of eigenvalues). The term-by-factor matrix describes the term loading to a specific latent factor. The document-by-factor describes the document loadings to a specific latent factor. The singular value illustrates the significance of a specific factor.

The performance of singular value decomposition in LSA in terms of simulation is almost similar to the way the human brain distills meaning in text [68]. It comes from the notion that some different words can have the same meaning or vice versa; one word in distinct contexts can have a different meaning. The words that have the same meaning will load to their common underlying concepts. This explains that one word might load multiple latent concepts in comparison to its main underlying concept. This is a key that empowers LSA in distinguishing the underlying concepts within textual data [68]. The more detailed mathematics can be found in prior studies [68,75].

4.2.4. Factor Determination

Singular Value Decomposition (SVD) can be calculated in different dimensions by eliminating the less important factors in the matrix. In addition, LSA can explain different levels of abstraction by decreasing the number of factors. In SVD there is a possibility to analyze data with different factors, which is usually is related to how much variance in the term vector is cumulatively explained by the factor [68,72]. However, the number of tokens in our study is too small to consider the variance and there are more specific tokens that need to be classified by the LSA. We calculated different dimensions to reach the ideal number of factors; in our study, the ideal number of the factors for the top level LSA analysis is five (Table 3).

Table 3. The five most important factors for machine tool selection and the high-loading terms.

Factors	High-Loading Terms
Factor 1	Rock, diamet, economi, weight, load, max, altern, kw, divers, secondary, conform
Factor 2	Consumpt, compat, energi, service, price, install, wast, multi, rel, power, technic, environment, space
Factor 3	Setup, product, custom. Integr, sub, eas, property, user
Factor 4	Mm, fig, shift, labor, rework, scrap, capit, pallet depreci, axi
Factor 5	Etc, cnc, rotary, adapt, tool, machin, deform, spindle, drive, failure, thermal, taper, environ, extinguish, fire

These five factors distinguish 57 tokens among 101 tokens in the word vector that specifically explain which words have been applied more.

4.2.5. Term Loadings and Cross-Loadings

As it is possible in exploratory factor analysis for one item to load multiple factors, in the LSA, one token might also load multiple factors. This comes from human language, in that one word may have different meanings according to context. For instance, the token "spindl" load from Factor 1 to Factor 5, respectively, as follows: 0.0295, 0.0045, −0.1682, 0.0547 and 0.1890. It shows that the token "spindl" were used in all factors but with different meanings or purposes, which made us decide to choose the high-loading term for each token in the five factors. Therefore, the token "spindl" was added to Factor 5 and the other loadings were named cross-loadings. Table 1 shows the high-loading terms after omitting the cross-loading terms (Appendix A shows all high-loading and cross-loading terms).

5. Results

5.1. Factor Interpretation and Labels

The meaning of each factor in Table 1 is explained by the terms and documents loaded to it. We created a new table (Table 4) that shows how these tokens describe sub-criteria in the MCDM framework. Now it is essential to label the factors and interpret the tokens. As it was mentioned in previous studies [68,72], labeling factors in LSA can be a challenging task, as usually there are no corresponding explanations or phrases in order to match to a specific factor. Labeling the criteria was decided by the authors. In addition, the authors read all the articles separately in order to realize the relation of each token and the previous literature. In this step, the authors read each token and found it in the literature in order to find out the most fitted sub-criterion, because each token does not make sense alone, and most of the sub-criteria are a mixture of some words. In some cases, making two or more tokens up concluded a sub-criterion; but, in some cases, merging a token and some other words out of Table 1 showed us the best and the most fitting sub-criterion. The first factor category or criterion is called "Size and Precision" because the tokens are referring to the previous studies that discussed the details. For example, ultimate load capacity, which is an important sub-criterion in machine tool selection, is considered as Precision. The second sub-criterion "diversity of materials and structure" discusses the changeability of a tool in terms of choosing materials or structure. Moreover, weight machine dimensions, maximum speed, maximum tool diameter and product conformance discus the size and precision at the same time. In some previous studies [77], Size and Precision were considered as two different criteria; however, in this study we show that they are meaningfully related to each other interchangeably. The second criterion is "Cost and Serviceability". Unlike the previous studies [77–79] that considered cost and serviceability as two different criteria, in this we demonstrate that these two criteria are somehow cause and effect elements. Price, energy consumption, maintenance cost, waste amount, operation cost, quality of technical service, service training and repair service are sub-criteria of the Cost and Serviceability criterion. The tool's flexibility has always been an important criterion in order to select an optimum choice. In machine tool selection, the literature setup time, installation easiness, ease of learning, ease of use, integration, properties and user friendliness fitted very well with the third classification of the tokens. "Productivity" is a well-known criterion in choosing all different type of machines and technologies. In this study, the best fitted tokens in the productivity classification are as follows: depreciation quality, scrap and rework reliability, pallet changer and fixture, labor cost as well as operation shifts. The last criterion, which is also is a mixture of two distinct criteria in prior studies, is called "Technical Features and Safety". These two criteria are straightly related to each other and it is better to consider them in a unique criterion. Because they are cause and effect criteria, the better and high-quality the technical features are, the higher the safety is, and vice versa. The most fitted tokens in the fifth classification and sub-criteria in the literature are as follows: capacity of rotary table, thermal deformation, spindle speed, spindle power, adaptability, failure rate, tool changer time, fire extinguisher, number of tappers and reliability of the drive system. These sub-criteria show that the most discussed type of machine tool was Computer Numerical Control (CNC). Regarding the literature, the previous studies that discussed the sub-criteria are displayed in Table 2. These references were concluded by SVD output in RapidMiner 9.6, and the results were classified based on high-term loadings in each factor; the related methodologies in each reference are demonstrated in Table 4.

Table 4. Criteria, sub-criteria, methodology and representative articles, according to the high-loading terms.

Criteria or Factors	Sub-Criteria or Sub Factor	Methodology	Representative Articles
Size and Precision	Ultimate load capacity, Diversity of materials and structure, Weight, Machine dimensions, Maximum speed, Maximum tool diameter, Product conformance,	Fuzzy DEMATEL and entropy weighting and later defuzzification VIKOR, fuzzy AHP and grey relational analysis, SWARA and COPRAS-G methods AHP Fuzzy ANP	[80] [79] [77] [81] [82]
Cost and Serviceability	Price, Energy consumption, Maintenance cost, Waste amount, Operation cost, Quality of technical service, Service training, Repair Service	ANP and grey relational analysis Fuzzy ANP and PROMETHEE AHP AHP TOPSIS and fuzzy ANP	[83] [84] [85] [86] [87]
Flexibility	Setup time, Installation easiness, Ease of learning, Ease of use, Integration, Properties, User friendliness,	Fuzzy ANP VIKOR AHP TOPSIS and fuzzy ANP Fuzzy ANP	[88] [89] [85] [87] [90]
Productivity	Depreciation quality, Scrap and rework reliability, Pallet changer and fixture, Labor cost, Operation shifts,	ANP and grey relational analysis Fuzzy ANP and PROMETHEE Fuzzy ANP AHP	[83] [84] [82] [91]
Technical Features and Safety	Capacity of rotary table, Thermal deformation, Spindle speed, Spindle power, Adaptability, Failure rate, Tool changer time, Fire extinguisher, Number of tapers, Reliability of drive system,	AHP and TOPSIS SWARA and COPRAS-G TOPSIS and fuzzy ANP Fuzzy ANP AHP	[92] [77] [87] [90] [85]

5.2. *Confluence of PMADM and Text mining*

As mentioned above, the application of text mining in PMADM is novel and has space to grow. The innovation in our results is that the prior studies presented each criterion separately, but the text mining approach shows that some criteria are interchangeably connected to each other based on prior literature containing Size and Precision, Cost and Serviceability, and Technical Features and Safety. The following Table 4 demonstrates the results of the Latent Semantic Analysis in finding the most discussed criteria in previous studies, which allow us to anticipate future research. In order to adjust the obtained tokens and sub-criteria, the authors needed to read all prior studies in detail to understand the relation between them.

6. Final Proposed Weighting Structure

In this section, each criterion and sub-criterion's weight will be calculated. As a result of the last section, sub-criteria were obtained based on a text-mining approach. With help of the LSA methodology, the most significant tokens were classified into five different categories, which are called the machine tool selection criteria. In the first step, the authors found the number of occurrences of each sub-criterion in the literature. For example, the phrase "Ultimate load capacity" were repeated in three different documents in the literature; thus, the number of occurrences were counted for each criterion and are shown in Table 5. In order to acquire each sub-criterion weight, the number of occurrences is summed in each criterion, and then every number of occurrences is divided by summation. This procedure is concluded by a decimal number that illustrates the sub-criterion weight. This procedure carries on for all criteria. For instance, the wight of the sub-criterion "Ultimate load capacity" is 0.11, which is obtained by the division of 3 by 27. To find out the criteria's weight, the last procedure was implemented in a higher level. The number of occurrences of each criterion was divided by the summation of all criteria. For example, the "Size and Precision" occurrences were 27, which was divided by the summation of all criteria, 149, with the result being 0.18. The other results are shown in Table 5.

The obtained results show us the importance of criteria in machine tool selection literature. Cost and Serviceability has the highest priority among the criteria, with 0.34 as the weight. The classification of criteria considering high priorities is identified as follows: (1) Cost and Serviceability; (2) Technical Features and Safety; (3) Size and Precision; (4) Flexibility; and (5) Productivity. Therefore, Table 5 displays the importance of each sub-criterion with its weight in order to find out the importance priority.

Generally, it is common to have a comparison between MADM methods to analyze the advantages and disadvantage of similar methods of weighting or ranking. This study presented a unique way of criteria selection and weighting, which is not based raw experts' opinions about a subject or topic.

Table 5. Criteria weighting based on the high-term loading in the Singular Decomposition Value.

Criteria	Sub-Criteria	Number of Occurrences	Sub-Criteria Weight	Criteria Weight
Size and Precision	Ultimate load capacity	3	0.11	0.18
	Diversity of materials and structure	2	0.07	
	Weight	6	0.22	
	Machine dimensions	6	0.22	
	Maximum speed	4	0.15	
	Maximum tool diameter	4	0.15	
	Product conformance	2	0.07	
Sum		27	1	

Table 5. *Cont.*

Criteria	Sub-Criteria	Number of Occurrences	Sub-Criteria Weight	Criteria Weight
Cost and Serviceability	Price	5	0.10	0.34
	Energy Consumption	5	0.10	
	Maintenance Cost	14	0.28	
	Waste amount	2	0.04	
	Operation Cost	8	0.16	
	Quality of Technical Service	1	0.02	
	Service training	10	0.20	
	Repair Service	5	0.10	
Sum		50	1	
Flexibility	Setup Time	4	0.18	0.15
	Installation easiness	6	0.27	
	Ease of Learning	3	0.14	
	Ease of Use	2	0.09	
	Integration	1	0.05	
	Properties	2	0.09	
	User Friendliness	4	0.18	
Sum		22	1	
Productivity	Depreciation Quality	3	0.23	0.1
	Scrap & Rework Reliability	3	0.23	
	Pallet Changer & Fixture	2	0.15	
	Labor Cost	3	0.23	
	Operation Shifts	2	0.15	
Sum		13	1	
Technical Features and Safety	Capacity of Rotary Table	5	0.14	0.25
	Thermal Deformation	5	0.14	
	Spindle Speed	4	0.11	
	Spindle Power	2	0.05	
	Adaptability	5	0.14	
	Failure Rate	4	0.11	
	Tool Changer Time	1	0.03	
	Fire Extinguisher	3	0.08	
	Number of Taper	4	0.11	
	Reliability of Drive System	4	0.11	
Sum		37	1	

7. Conclusions

As can be seen in Tables 4 and 5, the criteria selection andf weighting system was presented in a special case study, which was "Machine Tool Selection". This study showed how other researchers can apply text mining for the process of criteria selection and weighting in MADM and Prospective MADM. This new approach and model can be applied in many other cases and topics with bigger data bases. There are many proper data bases, such as Scopus, that can help to have more reliable answers and outputs for solving complicated decision-making problems. RapidMiner 9.6 is really powerful software in data and text mining, and as it was illustrated in the study, can be a convenient way to apply test mining methods for criteria selection and their weighting procedure.

In order to illustrate the importance of criteria selection and the weighting the criteria (referring to the MADM field), this study can be introduced as a new perspective in the literature review of weighting criteria, far from pairwise comparisons and policy-based decision-making models. This new approach can be applied with other newer contributions in the PMADM outline, such as "Multi-Aspect Criterion" or "Supportive-backup criteria", and still can be developed more with other tools and methods in text mining, or by adding newer items to the classic scheme of MADM in the wider area of the PMADM items and models.

Researchers in the field of MCDM can use this new framework as a new method for criteria selection and as a novel weighting system. Formerly, the MCDM field did not have any special way of criteria selection and many researchers tried to use social science methodologies to propose a proper way. From now on, this new proposed method can be applied in other decision-making problems, especially future-based ones like Prospective MADM models.

Author Contributions: Main idea, conceptualization, methodology, editing, discussion, and writing—original, S.H.Z.; conceptualization, text mining evaluation, case study, and writing—original, A.D. All authors have read and agreed to the published version of the manuscript.

Funding: Proyecto Nº 11190104: New approaches to the future-based decision making based on Prospective Multiple Attribute Decision Making (PMADM) outline; Programa Fodecyt, Conicyt, Ministrio de Educacion, Chile.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. High-loading and cross-loading terms.

Tokens	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
accuraci	−0.07544	−0.02045	−0.11645	−0.02227	0.019636
adapt	0.05399	−0.04528	0.003571	−0.14157	0.199365
administr	−0.02739	−0.04876	−0.00882	0.016549	−0.00983
altern	0.035358	−0.07187	−0.01185	−0.20609	0.014524
axi	−0.02261	0.00917	−0.16617	0.035082	0.095056
calibr	0.010538	−0.18789	0.004858	−0.04542	−0.03483
capabl	0.017671	0.005341	0.001862	−0.10701	0.049956
capit	−0.01365	−0.3049	0.01159	0.03833	−0.03655
choos	−0.03783	−0.00694	0.0011	−0.02371	0.018954
cnc	−0.01822	0.023044	−0.0021	0.026414	0.271168
collector	−0.00613	0.009799	0.005666	0.008668	0.123106
compani	−0.1016	0.002902	−0.01972	−0.10697	0.004729
compat	−0.21839	0.073125	0.010751	−0.07765	0.003632
conform	0.021347	−0.23393	0.00796	0.026274	−0.0212
consumpt	−0.13604	0.087801	−0.09374	−0.24513	−0.09154
cost	−0.17724	−0.29611	−0.0384	−0.14504	−0.05739
creat	−0.03566	−0.01711	−0.0005	−0.01023	−0.01453
custom	−0.02544	0.009187	0.014583	−0.02641	0.061236
deform	0.008177	0.017282	0.014448	0.005093	0.189623
depreci	0.019106	−0.30184	0.00804	0.035376	−0.02536
desir	−0.06595	0.008115	−0.00911	0.02126	0.063925
diamet	0.099029	−0.0026	−0.16178	−0.15385	0.015298

Table A1. *Cont.*

Tokens	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
divers	0.022183	−0.00125	0.001156	−0.10511	−0.00081
door	0.00085	0.000514	−0.00049	0.015471	0.080006
drive	0.011075	0.02959	0.021017	−0.04859	0.187868
durabl	−0.09892	0.016209	0.009514	−0.12024	−0.05007
eas	−0.10411	0.000595	0.013019	−0.03576	0.01473
economi	0.097927	−0.03463	−0.00437	−0.18764	0.026237
energi	−0.09209	0.071298	−0.00312	−0.22761	−0.07012
environ	−0.04275	0.0179	0.011725	−0.0469	0.160445
environment	−0.0535	0.029703	−0.00172	−0.19527	−0.03063
etc	0.15136	−0.04217	−0.03988	0.052489	0.471026
extinguish	0.001812	0.010433	0.004893	0.017118	0.156383
failur	−0.0148	0.011944	0.011471	−0.00073	0.178497
fig	−0.12019	−0.06003	−0.00246	0.062841	−0.01877
fire	0.001812	0.010433	0.004893	0.017118	0.156383
fixtur	−0.10158	−0.0179	−0.03705	−0.01674	−0.02785
gener	0.01332	−0.00645	−0.01385	0.004389	0.047838
imag	−0.05945	0.026555	0.004708	−0.08376	−0.0285
instal	−0.19012	0.04396	0.022779	−0.09798	0.042728
integr	−0.02544	0.009187	0.014583	−0.02641	0.061236
intend	−0.05033	0.005145	−0.005	0.012282	0.037751
inventori	−0.05286	−0.06489	−0.00272	0.014498	0.012564
invest	−0.11431	−0.03194	0.008617	−0.04711	−0.04063
kw	0.024839	−0.00395	−0.16872	0.025859	−0.02441
labor	−0.11883	−0.08484	0.013301	0.047077	−0.00877
length	0.016347	−0.00252	−0.15699	−0.03902	−0.0261
load	0.055425	−0.00905	0.001524	−0.12312	0.071062
lot	−0.06024	−0.06781	−0.00899	0.02154	0.001898
machin	−0.34665	−0.15065	−0.02262	0.033575	0.191764
manufactur	0.003534	−0.33313	−0.00022	0.013707	−0.00348
market	−0.06512	−0.03902	0.01068	−0.01209	−0.01693
max	0.053809	−0.01321	−0.15942	0.0453	0.078574
mcdm	−0.00424	0.011741	−0.00546	−0.10385	−0.01076
mist	−0.00613	0.009799	0.005666	0.008668	0.123106
mm	0.081566	−0.00395	−0.81775	0.097339	−0.14824
multi	−0.05101	0.040368	−0.00491	−0.14251	−0.04423
oper	−0.18888	−0.10804	0.003421	−0.02289	0.032413
pallet	−0.09463	−0.02823	−0.00904	0.036023	0.065802
paramet	0.001408	−0.02892	0.009004	−0.11643	0.017664
physic	−0.03349	−0.00185	−0.03829	0.006777	0.030456
power	0.004777	0.032131	−0.13564	−0.05492	0.110604

Table A1. *Cont.*

Tokens	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
previou	−0.04542	0.011221	0.002405	−0.07085	0.003702
price	−0.01604	0.052631	−0.12576	−0.20072	−0.04932
product	−0.17811	−0.13235	0.014905	−0.10792	0.050977
properti	0.003185	−0.02044	0.01204	−0.08363	0.0051
purchas	−0.05033	0.005145	−0.005	0.012282	0.037751
recycl	−0.02378	0.026506	0.011101	−0.06907	0.051117
rel	−0.01033	0.035153	0.015351	−0.13575	0.016411
rework	0.011429	−0.33022	0.007266	0.040113	−0.02494
rock	0.463096	−0.23186	−0.03155	−0.44445	0.130465
rotari	−0.00274	0.013883	−0.00411	0.023967	0.211357
safe	−0.05033	0.005145	−0.005	0.012282	0.037751
scrap	0.011429	−0.33022	0.007266	0.040113	−0.02494
secondari	0.022183	−0.00125	0.001156	−0.10511	−0.00081
secur	−0.05206	0.000298	0.00651	−0.01788	0.007365
servic	−0.20497	0.060389	−0.05111	−0.07789	0.149842
setup	−0.13246	−0.04561	0.022969	−0.15475	−0.05275
shape	−0.05785	0.017883	−0.03902	−0.03418	−0.01467
shift	−0.13133	−0.06672	0.01663	0.050026	−0.01085
space	−0.04351	0.027589	−0.04554	−0.05652	0.15348
spindl	0.0295	0.0045	−0.1682	0.0547	0.1890
standard	−0.06674	−0.01489	−0.11931	0.00499	−0.04856
stroke	−0.02433	0.014644	−0.14311	−0.01087	−0.03614
sub	0.007558	−0.24063	0.014101	0.004916	−0.02523
suppli	−0.02739	−0.04876	−0.00882	0.016549	−0.00983
taper	0.014388	0.005333	−0.00691	0.024307	0.171176
technic	−0.1124	0.030998	0.010576	−0.22095	−0.05604
technolog	−0.03303	0.013566	0.01132	−0.08502	−0.01854
thermal	−0.02329	0.012514	0.007474	0.005213	0.175115
tool	−0.26426	−0.04665	−0.23164	0.032951	0.197688
travers	0.009275	0.005969	−0.00797	0.00751	0.112826
unit	−0.05183	−0.0385	0.004586	0.000737	−0.01226
us	−0.10535	0.015706	−0.00151	0.005064	0.123736
user	−0.22003	0.049804	−0.05291	−0.08046	−0.03492
util	−0.06063	−0.22188	−0.0083	0.029607	−0.00313
variou	−0.04542	0.011221	0.002405	−0.07085	0.003702
volum	−0.00642	0.025635	0.008904	−0.13559	0.009527
warranti	−0.04616	0.027072	−0.00139	−0.07093	−0.02382
wast	−0.04027	0.042821	0.005618	−0.20761	−0.04861
weight	0.063673	0.014336	−0.04865	−0.22286	0.035649

References

1. Ho, W.; Xu, X.; Dey, P.K. Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *Eur. J. Oper. Res.* **2010**, *202*, 16–24. [CrossRef]
2. Keshavarz Ghorabaee, M.; Zavadskas, E.K.; Turskis, Z.; Antucheviciene, J. A new combinative distance-based assessment (CODAS) method for multi-criteria decision-making. *Econ. Comput. Econ. Cybern. Stud. Res.* **2016**, *50*, 25–44.
3. Zavadskas, E.K.; Turskis, Z. Multiple criteria decision making (MCDM) methods in economics: An overview. *Technol. Econ. Dev. Econ.* **2011**, *17*, 397–427. [CrossRef]
4. Kabir, G.; Sadiq, R.; Tesfamariam, S. A Review of Multi-criteria Decision-making Methods for Infrastructure Management. *Struct. Infrastruct. Eng.* **2014**, *10*, 1176–1210. [CrossRef]
5. Jahan, A.; Edwards, K.L. VIKOR method for material selection problems with interval numbers and target-based criteria. *Mater. Des.* **2013**, *47*, 759–765. [CrossRef]
6. Zavadskas, E.K.; Turskis, Z.; Kildiene, S. State of art surveys of overviews on MCDM/MADM methods. *Technol. Econ. Dev. Econ.* **2014**, *20*, 165–179. [CrossRef]
7. Ishizaka, A.; Labib, A. Review of the main developments in the analytic hierarchy process. *Expert Syst. Appl.* **2011**, *38*, 14336–14345. [CrossRef]
8. Scott, J.A.; Ho, W.; Dey, P.K. A review of multi-criteria decision-making methods for bioenergy systems. *Energy* **2012**, *42*, 146–156. [CrossRef]
9. Wang, Y.; Shi, X.; Sun, J.; Qian, W. A grey interval relational degree-based dynamic multi-attribute decision making method and its application in investment decision making. *Math. Probl. Eng.* **2014**. [CrossRef]
10. Aguezzoul, A. Third-party logistics selection problem: A literature review on criteria and methods. *Omega* **2014**, *49*, 69–87. [CrossRef]
11. Mardani, A.; Jusoh, A.; Zavadskas, E.K. Fuzzy multiple criteria decision-making techniques and applications – two decades review from 1994 to 2014. *Expert Syst. Appl.* **2015**, *42*, 4126–4148. [CrossRef]
12. Mardani, A.; Zavadskas, E.K.; Khalifah, Z.; Jusoh, A.; Nor, K.M.D. Multiple criteria decision-making techniques in transportation systems: A systematic review of the state of the art literature. *Transport* **2016**, *31*, 359–385. [CrossRef]
13. Zavadskas, E.K.; Mardani, A.; Turskis, Z.; Jusoh, A.; Nor, K.M.D. Development of TOPSIS Method to Solve Complicated Decision-Making Problems—An Overview on Developments from 2000 to 2015. *Int. J. Inf. Technol. Decis. Mak.* **2016**, *15*, 645–682. [CrossRef]
14. Saaty, T.L. *The Analytical Hierarchy Process*; McGraw-Hill: New York, NY, USA, 1980.
15. Saaty, T.L. *Decision making in Complex. Environments, the Analytical Hierarchy Process. for decision Making with Dependence and Dependence and Feedback*; RWS Publications: Pittsburgh, PA, USA, 1996.
16. Saaty, T.L. Fundamentals of analytic network process. In Proceedings of the The International Symposium on the Analytic Hierarchy Process, Cobe, Japan, 12–14 August 1999; pp. 348–379.
17. Keršulienė, V.; Zavadskas, E.K.; Turskis, Z. Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). *J. Bus. Econ. Manag.* **2010**, *11*, 243–258. [CrossRef]
18. Hashemkhani Zolfani, S.; Yazdani, M.; Zavadskas, E.K. An extended stepwise weight assessment ratio analysis (SWARA) method for improving criteria prioritization process. *Soft Comput.* **2018**, *22*, 7399–7405. [CrossRef]
19. Ginevicius, R. A New Determining Method for the Criteria Weights in Multi-Criteria Evaluation. *Int. J. Inf. Technol. Decis. Mak.* **2011**, *10*, 1067–1095. [CrossRef]
20. Rezaei, J. Best-worst multi-criteria decision-making method. *Omega* **2015**, *53*, 49–57. [CrossRef]
21. Pamučar, D.; Stević, Z.; Sremac, S. A new model for determining weight coefficients of criteria in MCDM models: Full consistency method (FUCOM). *Symmetry* **2018**, *10*, 393. [CrossRef]
22. Zavadskas, E.K.; Turskis, Z.; Vilutiene, T. Multiple criteria analysis of foundation instalment alternatives by applying additive ratio assessment (ARAS) method. *Arch. Civil. Mech. Eng.* **2010**, *10*, 123–141. [CrossRef]
23. Zavadskas, E.K.; Turskis, Z.; Antucheviciene, J.; Zakarevicius, A. Optimization of weighted aggregated sum product assessment. *Electron. Electr. Eng.* **2012**, *6*, 3–6. [CrossRef]
24. Keshavarz Ghorabaee, M.; Zavadskas, E.K.; Olfat, R.; Turskis, Z. Multi-Criteria Inventory Classification Using a New Method of Evaluation Based on Distance from Average Solution (EDAS). *INFORMATICA* **2015**, *26*, 435–451. [CrossRef]

25. Yazdani, M.; Zarate, P.; Zavadskas, E.K.; Turskis, Z. A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems. *Manag. Decis.* **2019**, *57*, 2501–2519. [CrossRef]
26. Stević, Z.; Pamucar, D.; Puska, A.; Chatterjee, P. Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS). *Comput. Ind. Eng.* **2020**, *120*, 106231. [CrossRef]
27. Hashemkhani Zolfani, S.; Bahrani, M. Investment prioritizing in high tech industries based on SWARA-COPRAS approach. *Technol. Econ. Dev. Econ.* **2014**, *20*, 534–553. [CrossRef]
28. Hashemkhani Zolfani, S.; Aghdaie, M.H.; Derakhti, A.; Zavadskas, E.K.; Morshed Varzandeh, M.H. Decision making on business issues with foresight perspective; An application of new hybrid MCDM model in shopping mall locating. *Expert Syst. Appl.* **2013**, *40*, 7111–7121. [CrossRef]
29. Hashemkhani Zolfani, S.; Esfahani, M.H.; Bitarafan, M.; Zavadskas, E.K.; Lale Arefi, S. Developing a new hybrid MCDM method for selection of the optimal alternative of mechanical longitudinal ventilation of tunnel pollutants during automobile accidents. *Transport* **2013**, *28*, 89–96. [CrossRef]
30. Chini, M.; Lale Arefi, S.; Hashemkhani Zolfani, S.; Ustinovicius, L. Choosing a proper method for strengthening WPC beams with grooving method using SWARA-EDAS. *Arch. Civ. Eng.* **2018**, *64*, 161–174. [CrossRef]
31. Hashemkhani Zolfani, S.; Mosharafiandehkordi, S.; Kutut, V. A pre-planning for hotel locating according to the sustainability perspective based on BWM-WASPAS approach. *Int. J. Strateg. Prop. Manag.* **2019**, *23*, 405–419. [CrossRef]
32. Hashemkhani Zolfani, S.; Ecer, F.; Pamucar, D.; Raslanas, S. Neighborhood selection for a newcomer via a novel BWM-based revised MAIRCA integrated model: A case from the Coquimbo-La Serena conurbation, Chile. *Int. J. Strateg. Prop. Manag.* **2020**, *24*, 102–118. [CrossRef]
33. Opricovic, S.; Tzeng, G.H. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *Eur. J. Oper. Res.* **2004**, *156*, 445–455. [CrossRef]
34. Keshavarz Ghorabaee, M.; Amiri, M.; Zavadskas, E.K.; Turskis, Z.; Antucheviciene, J. A Comparative Analysis of the Rank Reversal Phenomenon in the EDAS and TOPSIS Methods. *Econ. Comput. Econ. Cybern. Stud. Res.* **2018**, *52*, 121–134. [CrossRef]
35. Hashemkhani Zolfani, S.; Chatterjee, P. Comparative Evaluation of Sustainable Design Based on Step-Wise Weight Assessment Ratio Analysis (SWARA) and Best Worst Method (BWM) Methods: A Perspective on Household Furnishing Materials. *Symmetry* **2019**, *11*, 74. [CrossRef]
36. Deveci, M.; Canitez, F.; Gokasar, I. WASPAS and TOPSIS based interval type-2 fuzzy MCDM method for a selection of a car sharing station. *Sustain. Cities Soc.* **2018**, *41*, 777–791. [CrossRef]
37. Zhao, H.; Guo, S.; Zhao, H. Comprehensive assessment for battery energy storage systems based on fuzzy-MCDM considering risk preferences. *Energy* **2019**, *168*, 450–461. [CrossRef]
38. Keshavarz Ghorabaee, M.; Amiri, M.; Zavadskas, E.K.; Turskis, Z.; Antucheviciene, J. A new hybrid fuzzy MCDM approach for evaluation of construction equipment with sustainability considerations. *Arch. Civ. Mech. Eng.* **2018**, *18*, 32–49. [CrossRef]
39. Dincer, H.; Yuksel, S. An integrated stochastic fuzzy MCDM approach to the balanced scorecard-based service evaluation. *Math. Comput. Simul.* **2019**, *166*, 93–112. [CrossRef]
40. Boral, S.; Howard, I.; Chaturvedi, S.K.; McKee, K.; Naikan, V.N.A. An integrated approach for fuzzy failure modes and effects analysis using fuzzy AHP and fuzzy MAIRCA. *Eng. Fail. Anal.* **2020**, *108*, 104195. [CrossRef]
41. Roozbahani, A.; Ghased, H.; Hashemi Shahedany, M. Inter-basin water transfer planning with grey COPRAS and fuzzy COPRAS techniques: A case study in Iranian Central Plateau. *Sci. Total Environ.* **2020**, 138499. [CrossRef]
42. Pamučar, D.; Deveci, M.; Canitez, F.; Bozanic, D. A fuzzy Full Consistency Method-Dombi-Bonferroni model for prioritizing transportation demand management measures. *Appl. Soft Comput.* **2020**, *87*, 105952. [CrossRef]
43. Rahimi, S.; Hafezalkotob, A.; Monavari, S.M.; Hafezalkotob, A.; Rahimi, R. Sustainable landfill site selection for municipal solid waste based on a hybrid decision-making approach: Fuzzy group BWM-MULTIMOORA-GIS. *J. Clean. Prod.* **2020**, *248*, 119186. [CrossRef]
44. Hashemkhani Zolfani, S.; Maknoon, R.; Zavadskas, E.K. An introduction to Prospective Multiple Attributes Decision Making (PMADM). *Technol. Econ. Dev. Econ.* **2016**, *22*, 309–326. [CrossRef]
45. Ozernoy, V.M. Multiple criteria decision making in the USSR: A survey. *Nav. Res. Logist.* **1988**, *35*, 543–566. [CrossRef]

46. Leong, T.Y. Multiple perspective dynamic decision making. *Artif. Intell.* **1998**, *105*, 209–261. [CrossRef]
47. Salo, A.; Gustafsson, T.; Ramanathan, R. Multi-criteria methods for technology foresight. *J. Forecast.* **2003**, *22*, 235–255. [CrossRef]
48. Xu, Z.; Yager, R. Dynamic intuitionistic fuzzy multi-attribute decision making. *Int. J. Approx. Reason.* **2008**, *48*, 246–262. [CrossRef]
49. Campanella, G.; Ribeiro, R.A. A framework for dynamic multiple-criteria decision making. *Decis. Support Syst.* **2011**, *52*, 52–60. [CrossRef]
50. Trutnevyte, E.; Stauffacher, M.; Scholz, R.W. Linking stakeholder visions with resource allocation scenarios and multi-criteria assessment. *Eur. J. Oper. Res.* **2012**, *219*, 762–772. [CrossRef]
51. Arms, H.; Wiecher, M.; Kleiderman, V. Dynamic models for managing big decisions. *Strategy Leadersh.* **2012**, *40*, 39–46. [CrossRef]
52. Zhang, Z. An approach to dynamic multi-attribute decision making for choosing green supplier. *J. Converg. Inf. Technol.* **2012**, *7*, 261–269.
53. Tadic, S.R.; Zecevic, S.M.; Krstic, M.D. Ranking of logistics system scenarios for central business district. *Promet Traffic Transp.* **2014**, *26*, 159–167.
54. Gonzalez-Prida, V.; Viveros, P.; Barbera, L.; Crespo Marquez, A. Dynamic analytic hierarchy process: AHP method adapted to a changing environment. *J. Manuf. Technol. Manag.* **2014**, *24*, 457–475. [CrossRef]
55. Ondrus, J.; Bui, T.; Pigneur, Y. A Foresight Support System Using MCDM Methods. *Group Decis. Negot.* **2014**, *24*, 333–358. [CrossRef]
56. Jassbi, J.J.; Ribeiro, R.A.; Varela, L.R. Dynamic MCDM with future knowledge for supplier selection. *J. Decis. Syst.* **2014**, *23*, 232–248. [CrossRef]
57. Hashemkhani Zolfani, S.; Maknoon, R.; Zavadskas, E.K. Multiple Attribute Decision Making (MADM) based scenarios. *Int. J. Strateg. Prop. Management* **2016**, *20*, 101–111. [CrossRef]
58. Hashemkhani Zolfani, S.; Dehnavieh, R.; Poursheikhali, A.; Prentkovskis, O.; Khazaelpour, P. Foresight Based on MADM-Based Scenarios' Approach: A Case about Comprehensive Sustainable Health Financing Models. *Symmetry* **2020**, *12*, 61. [CrossRef]
59. Hashemkhani Zolfani, S.; Maknoon, R.; Zavadskas, E.K. MADM and Futures Studies; A necessity. In Proceedings of the 9th International Scientific Conference "Business and Management 2016", Vilnius Gediminas Technical University Vilnius, Lithuania, 12–13 May 2016; pp. 1–7. [CrossRef]
60. Hashemkhani Zolfani, S.; Zavadskas, E.K.; Khazaelpour, P.; Cavallaro, F. The Multi-Aspect Criterion in the PMADM Outline and Its Possible Application to Sustainability Assessment. *Sustainability* **2018**, *10*, 4451. [CrossRef]
61. Hashemkhani Zolfani, S.; Masaeli, R. *From Past to Present and into the Sustainable Future; PMADM Approach in Shaping Regulatory Policies of the Medical Device Industry in the New Sanction Period*; Sustainability Modeling in Engineering; A multi-Criteria Perspective; Chatterjee, P., Yazdani, M., Chakraborty, S., Eds.; Word Scientific: Singapore, 2019.
62. Hashemkhani Zolfani, S.; Yazdani, M.; Zavadskas, E.K.; Hasheminasab, H. Prospective MADM and sensitivity analysis of the experts based on Causal Layered Analysis (CLA). *Ekon. a Manag.* **2020**. In press.
63. De Miranda Santo, M.; Massari Coelho, G.; Maria dos Santos, D.; Fellos Filho, L. Text mining as a valuable tool in foresight exercises: A study on nanotechnology. *Technol. Forecast. Soc. Chang.* **2006**, *73*, 1013–1027. [CrossRef]
64. Saritas, O.; Burmaoglu, S. The evolution of the use of Foresight methods: A scientometric analysis of global FTA research output. *Scientometrics* **2015**, *105*, 497–508. [CrossRef]
65. Jungermann, F.; Information Extraction with RapidMiner. GSCL Symposium Sprachtechnologie Und EHumanities. 2009, p. 1. Available online: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.184.1826&rep=rep1&type=pdf#page=59 (accessed on 19 May 2020).
66. Hotho, A.; Nürnberger, A.; Paaß, G. A Brief Survey of Text Mining. *Gldv J. Comput. Linguist. Lang. Technol.* **2005**, *20*, 19–62.
67. Delen, D.; Crossland, M.D. Seeding the survey and analysis of research literature with text mining. *Expert Syst. Appl.* **2008**, *34*, 1707–1720. [CrossRef]
68. Sidorova, A.; Evangelopoulos, N.; Valacich, J.S.; Ramakrishnan, T. Uncovering the Intellectual Core of the Information Systems Discipline. *Mis Q.* **2008**, *32*, 467–482. [CrossRef]
69. Han, J.; Kamber, M.; Pei, J. *Data Mining Techniques*, 3rd ed.; Elsevier: New York, NY, USA, 2011.

70. Li, Y.; Joshi, K.D. The state of social computing research: A literature review and synthesis using the latent semantic analysis approach. In Proceedings of the 18th Americas Conference on Information Systems 2012, Seattle, DC, USA, 9–11 August 2012; Volume 1, pp. 33–40.
71. Hossain, M.M.; Prybutok, V.; Evangelopoulos, N. Causal Latent Semantic Analysis (cLSA): An Illustration. *Int. Bus. Res.* **2011**, *4*, 38–50. [CrossRef]
72. Lin, X.; Li, Y.; Wang, X. Social commerce research: Definition, research themes and the trends. *Int. J. Inf. Manag.* **2017**, *37*, 190–201. [CrossRef]
73. Morley, J. The Academic Phrasebank_ An Academic Writing Resource for Students and Researchers. The University of Manchester: Manchester, UK, 2017.
74. Kotu, V.; Deshpande, B. *Data Science 2nd Edition Concepts and Practice*; Elsevier: New York, NY, USA, 2018.
75. Baker, K. *Singular Value Decomposition Tutorial*; Working Paper; Ohio State University: Columbus, OH, USA, 2013; pp. 1–24.
76. Klema, V.; Laub, A. The singular value decomposition: Its computation and some applications. *IEEE Trans. Autom. Control* **1980**, *25*, 164–176. [CrossRef]
77. Aghdai, M.H.; Hashemkhani Zolfani, S.; Zavaskas, E.K. Decision making in machine tool selection: An integrated approach with SWARA nad COPRAS-G method. *Inz. Ekon. Eng. Econ.* **2014**, *24*, 5–17. [CrossRef]
78. Önüt, S.; Kara, S.S.; Efendigil, T. A hybrid fuzzy MCDM approach to machine tool selection. *J. Intell. Manuf.* **2008**, *19*, 443–453. [CrossRef]
79. Samvedi, A.; Jain, V.; Chan, F.T.S. An integrated approach for machine tool selection using fuzzy analytical hierarchy process and grey relational analysis. *Int. J. Prod. Res.* **2012**, *50*, 3211–3221. [CrossRef]
80. Hai, L.; Wang, W.; Fan, L.; Li, Q.; Chen, X. A novel hybrid MCDM model for machine tool selection using fuzzy DEMATEL, entropy weighting and later defuzzification VIKOR. *Appl. Soft Comput. J.* **2020**, *91*, 106207. [CrossRef]
81. Yurdakul, M. AHP as a strategic decision-making tool to justify machine tool selection. *J. Mater. Process. Technol.* **2004**, *146*, 365–376. [CrossRef]
82. Myint, S.; Tabucanon, M.T. A multiple-criteria approach to machine selection for flexible manufacturing systems. *Int. J. Prod. Econ.* **1994**, *33*, 121–131. [CrossRef]
83. Matijevi&#x107, M.; Mrvac, N.; Mikota, M. The effect of expansion and simultaneous contrast in modificated figural dotted and groundal dotted illusions. *Teh. Vjesn.* **2014**, *21*, 1297–1301. [CrossRef]
84. Özceylan, E.; Kabak, M.; Dadeviren, M. A fuzzy-based decision making procedure for machine selection problem. *J. Intell. Fuzzy Syst.* **2016**, *30*, 1841–1856. [CrossRef]
85. Arslan, M.Ç. A Decision Support System for Machine Tool Selection. Master's Thesis, Sabanci University, Istanbul, Turkey, 2002.
86. Çimren, E.; Çatay, B.; Budak, E. Development of a machine tool selection system using AHP. *Int. J. Adv. Manuf. Technol.* **2007**, *35*, 363–376. [CrossRef]
87. Ayag, Z.; Gürcan Özdemir, R. Evaluating machine tool alternatives through modified TOPSIS and alpha-cut based fuzzy ANP. *Int. J. Prod. Econ.* **2012**, *140*, 630–636. [CrossRef]
88. Kumru, M.; Kumru, P.Y. A fuzzy ANP model for the selection of 3D coordinate-measuring machine. *J. Intell. Manuf.* **2015**, *26*, 999–1010. [CrossRef]
89. Hafezalkotob, A.; Hafezalkotob, A. Interval target-based VIKOR method supported on interval distance and preference degree for machine selection. *Eng. Appl. Artif. Intell.* **2017**, *57*, 184–196. [CrossRef]
90. Ayağ, Z.; Özdemir, R.G. An intelligent approach to machine tool selection through fuzzy analytic network process. *J. Intell. Manuf.* **2011**, *22*, 163–177. [CrossRef]
91. Lin, Z.C.; Yang, C.B. Evaluation of machine selection by the AHP method. *J. Mater. Process. Technol.* **1996**, *57*, 253–258. [CrossRef]
92. Xia, Y.M.; Lin, L.K.; Wu, D.; Jia, L.H.; Chen, Z.; Bian, Z.K. Geological adaptability matching design of disc cutter using multicriteria decision making approaches. *J. Cent. South. Univ.* **2018**, *25*, 843–854. [CrossRef]