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Smart Competence Management Using Business Analytics with Fuzzy Predicates

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Abstract: Organizations consider human capital as one of their most important assets. Experts in the field have focused on the research and development of human talent management skills. At present, companies are giving high importance to the management of this intangible resource. Management by competencies and skills is basic in the selection and development of the most valuable asset the organization has: its human capital. A conceptual framework of the intelligent management of human capital and some more advanced knowledge discovery techniques are presented in this paper. A methodology for smart detection of core competencies based on fuzzy logic predicates and business analytics is proposed. The proposed methodology allows: (1) the evaluation of the importance of competencies, (2) the identification of competencies achievement level of each employee, (3) the identification of competencies with difficulties, (4) the identification of competencies that have influence on others, and (5) a hierarchization of the competencies to select the most appropriated for the employee recruitment plan. Furthermore, an analysis is proposed using knowledge discovery, which allows one to identify which competences have influence on a specific one. All of the above is useful to build an ideal profile for a position. A case study was carried out in order to show the implementation and interpretation of our proposal.

Keywords: compensatory fuzzy logic; human capital management; business analytics

MSC: 68T20

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1. Introduction

Business analytics is a term that was made popular by the findings of Davenport and Harris in their book *Competing on Analytics: The New Science of Winning* [1]. The authors describe how business leaders use information systems, statistical analysis, and predictive models to strategically lead their organizations. In a broad sense, business analytics includes gathering, processing, and analyzing data using a variety of methods, communicating the results of the analysis, and matching them to key strategic goals [2]. The use of statistics, artificial intelligence, and other sophisticated mathematical and computer science technics are used to find useful knowledge regarding markets and internal performance, which will lead towards better decision making within companies. In this sense, business analytics has been a useful tool for managers for making good and better decisions based on concrete data. Business analytics looks for decision making through knowledge discovery and knowledge engineering. Fuzzy predicates business analytics have been reported as a useful way to achieve this, such as in [3]. Important data could be processed with fuzzy logic to help managers to discover useful knowledge and develop better strategies according to the main goals of companies.

On the other hand, the importance of human capital has been recognized as a relevant element for the achievement of company results using methodologies that help to make better decisions. Therefore, the following research question emerges: What kind of methods and elements should be considered in smart competence management? Particularly, knowledge concerning a hierarchy of competencies and their interactions are very important in the area of human capital management, and specifically in core competencies detection, such as in [4].

One of the most important questions that arise during the recruitment of a new employee is: how to select the best candidate and what competencies the candidate should have according to the company. Here, an opportunity gap appears for recruiters to make the best decisions. The most important decision-making tasks included in human capital management are the development of competence profiles, performance evaluation of employees, procedures to measure gaps between real and expected performance, and evaluations of intentional development plans. The selection of core competencies is a key factor in all these decisions [5].

In this stage, the human resource department (HRD) of the company plays an important role, because here is where the recruitment strategies are developed. Fang & Qi [6] comment "in the competitive service industry, the focus is on the human resource development of recruiting strategies that attract only those personnel that match best to the jobs, and to retain and motivate those employees that stay with the company. Also, the HRD must develop reward and recognition systems to help maintain high morale and teamwork spirit that contribute to the unique quality factor of every excellent service company" (p. 1).

Business analytics is a set of tools that can be used to try to answer the above questions, and fuzzy logic has become a useful management tool to uncover knowledge and evaluate predicates. Therefore, in this work, a methodology based on fuzzy logic is proposed to help senior management develop better training plans for the company employees and new staff, as well as to identify the best candidate for a new position. We evaluate different competencies and identify the most important ones in order to provide valuable information to the senior management. The proposed methodology uses fuzzy predicate-based knowledge discovery and knowledge engineering to help managers to make smart decisions on recruitment.

The paper is structured as follows: Section 2 shows a brief literature review. In Section 3 a conceptual framework is shown where the concepts of human capital and business intelligence, as well as several methods, are described. Section 4 contains the proposed methodology with fuzzy logic implementation. Section 5 includes a general overview of the obtained results from the application of the proposed methodology into a company. Finally, Section 6 shows the conclusions and recommendations for further research.

2. Background

Human capital is one of the most important assets that managers focus on. Wang & Jiang [7] state that the human resource of an enterprise acts as a valuable resource, and managers continually pay more and more attention to it. Because of its potential for the company, senior managers are becoming more involved in the research on human capital in order to get insights that allow their organizations to grow and reach their objectives. Human capital is essential for all organizations; investments focused on human capital are crucial to firm value generation and successful completion of its projects. There is so much information regarding human capital, but the most important dimension is the one related to competencies: "by developing competence, organizations have the opportunity to apply it to the recruitments process, educational training, performance management, job transfers or promotions, successor programs, talent inventory, employee career development, and human resource overall performance" [8] (p.2). For this reason, many researchers have focused their work on human capital, its study, measure, and improvement. Some of these studies involve the use of different analytics techniques, such as the analytic hierarchy process (AHP), fuzzy logic, or neural networks [9]. Some studies focus on the analysis of specific employee skills for a determined position [10]. According to Ahmed et al. [11], there are several studies that appear to analyze human capital management, and there are a few dedicated to studying and evaluating the specific competencies and skills of the employees. There are some elements that senior management consider important or necessary to recruit new employees; these multi-attributes require good precision analysis techniques to help decision makers (DM) make the best decisions. AHP is one of the most common methods used to study several attributes; it is a powerful tool that seeks a systematic practice to define priorities and support complex decision making [12,13]. However, there are other important techniques of multi-criteria analysis such as fuzzy AHP and TOPSIS [12,14]. The "multi-criteria decision analysis (MCDA) is a widely used basic method that groups a collection of formal approaches that take into account multiple criteria and help decision makers explore decisions when intuitive, gut-feeling decision making is not satisfactory" [15] (p. 265). In the MCDA framework, other techniques that not only consider the individual characteristics of each alternative of a choice of subsets of alternatives, but also their positive or negative interrelations are also used. These methods include the Elimination Et Choix Traduisant la Realite (ELECTRE) method, which is essentially composed of MCDA methods according to what experts have called the French or European school. ELECTRE 1 was the first of a series to be developed. ELECTRE methods can be applied to decision problems where a DM may need support [16]. Another method is called the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), which determines the extent to which an alternative is better than the rest and involves few mathematical computations and complex preference functions [17]. Value or utility function-based methods, such as the multi-attribute utility theory (MAUT), are used to compare information by substituting that information with an arbitrary measure called *utiles* [18]. The utile values range from 0 to 1, with intermediate values decided by the DM. The identified critical metrics are plotted on a graph from 0 (worst case) to 1 (best case). Then, a utility curve is plotted to model the subjective value of each outcome [18]. The method called the Simple additive weighting (SAW) algorithm is known as the weighted sum algorithm and it is probably the best known and most widely used within multiple-attribute decision making (MADM) methods [19]. The basic logic of SAW is to obtain a weighted sum of the performance ratings of each alternative over all attributes [20]. In the following, a brief description of the main used methods is presented.

2.1. Analytic Hierarchy Process (AHP)

Some studies have focused on the difficulty that managers and recruiters have in making good decisions, where they must evaluate several criteria to select the best employee or candidate for a position. To reach this objective, some studies define a different kind of criteria and create some structured decision hierarchy to evaluate it based on a main goal. The AHP is a structured technique that works with this methodology because it decomposes the decision problem into mathematical objectives and multi-criteria that affects the achievement of the target. By doing this, the quantitative and qualitative aspects of the problem at all levels could be explored to find the priority [21].

The disadvantage of this multi-criteria methodology is that it requires that the DM provides subjective assessments regarding the relative importance of each of the criteria, and also the need to specify his preference for each criterion and each decision alternative [22].

2.2. Fuzzy AHP

Another perspective to consider in this study is the one that focuses on weighting the preferences for the evaluation of some human capital dimensions. Fuzzy logic techniques are good for this purpose, and this is why they are applied to some multicriteria methods like AHP. In fact, Chou et al. [14] mention that a fuzzy technique is beneficial for solving complicated decision problems, where the problem is decomposed into different hierarchy levels of criteria. Fuzzy logic methodologies focus on the catch of the empirical knowledge to evaluate it and transform it into useful knowledge. "This characteristic allows that fuzzy logic works with some qualitative and quantitative data and, combined with some multi-criteria methods, shows better results. Its data requirement is minimal and it is capable of handling multiple objectives for R&D (research and development) projects and decomposing the problem into multilevel structure or hierarchy" [23] (p. 1156).

2.3. AHP and TOPSIS

The integration of multi-criteria methods with the Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS) has been performed in several research papers, such as in [14]. One of the most common integrations is the hybrid method of AHP with TOPSIS. Emrouznejad & Marra [12] remark that "AHP is used to weight (the relative importance of) the dimensions and their sub-components; then weights and performance scores are combined using TOPSIS. This integration has been applied successfully to the complex problem of the vague and imprecise nature of linguistic assessments in the case of facility location selection" (p. 6664).

Multi-criteria decision-making methods are easy to use and flexible, and they can work with complex problems. The main advantages of these methods are that they can consider different levels of importance for different criteria [12] and they can process them by assigning them several weights. Some techniques, such as TOPIS, manage, in a better way, the assignment of weights, although this methodology does not propose a general perspective for identification and evaluation. Therefore, TOPSIS cannot be used directly to identify and evaluate the competencies that employees must possess, or that candidates should have for a position. It is difficult to consider many factors at a time to evaluate the performance of employees in an organization. In this case, Fuzzy logic can be used, because it considers multiple input parameters with the uncertainty of each factor [11].

In this paper, we focus on working with the compensatory fuzzy logic predicates that will allow one to represent the natural language. This approach would facilitate the expectations of the interested staff and would help to redesign the structure of the system in case this was required by those involved in the project.

3. Conceptual Framework

Recently, organizations and business companies are focused on improving their management processes by implementing more efficient tools regarding data analysis. In fact, many organizations have implemented Information Technology (IT) tools that help them to make better decisions. Oesterreich & Teuteberg [24] mention that some industries are being shaped by an ongoing IT-enabled transformation process, with far-reaching consequences on their structures and business processes. Moreover, organizations are getting more interested in the application of BA resources in order to remain competitive [25].

Business analytics begins with a dataset or commonly with a database, and as the database grows, the difficulty of managing information increase. Sedkaoui [26] states that business analytics goes beyond plain analytics, requiring a clear knowledge of the business. BA is used to increase productivity and support almost all the crucial areas of the organization. Bedeley et al. [25] mention that "analytics is mostly used to improve the value generated by the primary activities of the value chain such as marketing or sales, but also in the case of supporting activities, analytics has very good applications in human resource management compared to other activities" (p. 7).

The Human Resource Department (HRD) is a very important area in any organization because here is where the employees are recruited and become a valuable intangible asset. Therefore, good management of this area should help the organization to reach their strategic goals in a significant way. Stavrou et al. [27] state that Human Resource Management (HRM) is a competitive tool that is crucial for the development of organizational competitive advantages. The relation between HRM and organizational performance has been the subject of systematic research, because the impact in all the activities depends on attracting and retaining valuable workforces that perform their duties at a high level in order to achieve organizational goals [28]. In HRD, there are many important management functions, but one of the most important is human resource planning, which considers new recruitment activities, such as defining the competencies that new employees should have, according to the organization. According to Silva [29] Human Capital (HC) "has become an important focus for the general management, because it refers to useful skills, knowledge, competencies, and other attributes that enhance an individual's productivity in the labor market and facilitate other forms of personal and social wellbeing" (p. 1). Business analytics can use human capital unstructured data to derive actionable talent management insights to drive and improve business performance and optimize every stage of the company talent cycle [30].

The acquisition and transformation of knowledge in the organizations is an inherently human process; therefore, HC is an important source of sustained competitive advantage [31]. There is a current trend in project management that has a strong relationship with the HRM, where HC dimensions include project skills (e.g., abilities, knowledge, and capacities) [32]. According to Schulz et al. [33] employees' education, training, and experience allow them to be more efficient and inventive in their work performance.

Related to this, there are so many competencies or skills that employees should have to develop their jobs. In this sense, general management competencies have more importance, because the senior management should be responsible for the big decisions that would have a positive or negative impact on the company. As Bharwani & Talib [34] state, "The general manager's role demands sophisticated talent, with global acumen, multi-cultural perspective, people-handling skills, technological proficiency, strategic and entrepreneurial skills and the ability to manage an increasingly delayered organization. Despite the significance of his role, there is limited research undertaken to understand the essential competencies and capabilities required by the general manager for leadership and management success" (p. 394).

On the other hand, the data analytics paradigm has evolved towards the active use of Augmented Intelligence, and it has been called Augmented Analytics. Within the framework of this new paradigm, the Eureka Universe-The Universal Analyst software has been developed [35]. It is a unique business analytics intelligent system that allows one to solve the following independent tasks and mix them towards decision making problem solutions without needing any user's knowledge regarding mathematics, computer sciences theories, and algorithms; only their own knowledge concerning the business and common sense are required for the interaction with a graphical editor based on natural language.

Some tasks that could be solved independently and mixed towards business decision making problems solutions are:

- Evaluation of systems and processes by knowledge based semantic indexes;
- Decision support and analysis;
- Explicit models of expert knowledge;
- Knowledge discovery from data;
- Reasoning to discover new knowledge;
- Inference, forecast, and systems simulation based on the discovered knowledge.

In this research, the data analysis was processed with the Eureka-Universe software. Eureka-Universe can perform the following tasks:

- Evaluation task—The truth values of a fuzzy predicate are computed from a dataset;
- Discovery task—It looks for relationships between the linguistic states of a dataset (fuzzy predicates) that meet user specifications. This search is carried out using genetic algorithms to adjust the parameters of membership functions defined in linguistic states;
- Inference task—A discovery task on a dataset in which the linguistic states of condition and decision variables have been defined is first performed. The fuzzy predicates obtained are used to infer the values of the decision variables from another dataset in which only the condition variables are known.

This software is used to evaluate new theoretical developments such as Compensatory Fuzzy Logic [36] and, more recently, Archimedean Compensatory Fuzzy Logic [37], which are transdisciplinary theories with excellent properties for interpretability with language.

These features are exploited in this research using the available knowledge in human and documentary data sources to create fuzzy logic predicates, which brings us closer to studying decision-oriented augmented analytics.

4. Proposed Methodology

The following methodology proposes the use of business analytics to help decision-makers in the recruitment process in the Human Resource Department. This methodology is summarized as follows:

- Defining a set of several competencies which are important for the organization;
- Following the proposed evaluation predicates;
- Performing the proposed actions for the knowledge discovery process;
- Evaluating these evaluation predicates and actions with data of the organization;
- Analyzing the results and setting out "the best" employee recruitment plan for the organization.

4.1. Evaluation Predicates

The evaluation predicates presented here start with the proposal of fuzzy logic predicates that deals with the key aspects usually considered in any HRD. Furthermore, actions to determine the influence that competencies have among them are also described in fuzzy logic predicates. These fuzzy predicates are then evaluated by the information found in local databases and documentary data sources for a particular organization. Finally, a well-funded decision for the development of an employee recruitment plan for that organization can be performed. This methodology allows making decisions related to competence management activities in the organization through the flow of the knowledge tasks mentioned above.

The most significant problems of decision making inside the organization that are included in this methodology are: competencies hierarchization, evaluation of the employees based on stablished competencies profiles, and the development of training plans. The competencies profiles shown in Appendix A are used as starting points and are classified as behavioral competencies, motivational competencies, and professional competencies.

Assuming the DM already have a list of competencies as a starting point, it is necessary to select (according to the experts in the organization) which of them are going to be considered in the recruitment process. The following fuzzy predicates focus on the main aspects of HRD and are proposed to collect and evaluate the opinion of all people involved.

Evaluation Predicate 1: Important competencies

First, it is necessary to identify the "most important competencies" for the company. The relative importance of competencies is evaluated with the truth value of the predicate $I(i)$: "All the experts consider that the i competency is important". This means that if each expert considers that the i competency is aligned to the organization goals, then it is assumed that the i competency is considered as important by the expert. This is shown in the next expression as:

$$I(i) = \forall k\, [Al(k,i) \rightarrow Im(k,i)] = \bigwedge_{k=1}^{n_e} [Al(k,i) \rightarrow Im(k,i)] \tag{1}$$

where n_e is the number of experts, $Al(k,i)$ is the truth value of the assertion "expert k considers i competency is aligned to the organization goals", and $Im(k,i)$ is the truth value of the assertion "expert k considers i competency as important". Here, $\wedge$ is used to denote the conjunction operator. Equation (1) shows that it is possible to express the same predicate in different ways. Equation (1) can be read as "i competency will be considered as important if: (a) (First part of the equation) all the experts consider that i competency is aligned to the organization goals and therefore important for it"; or (b) (Second part of equation) expert 1 considers that i competency is aligned to the organization goals and therefore important for it AND expert 2 considers that i competency is aligned to the organization goals and is therefore important for it, AND so on.

Evaluation Predicate 2: Personal performance

Each employee is then evaluated by their own level of competence accomplishments. This can be done with the truth value of the predicate $E(j)$: "The j employee has a good evaluation in all the competencies". This means the more important the competency, the better the employee's performance. This is shown in the next expression as:

$$E(j) = \forall n\ [I(n) \rightarrow Gp(j,n)] = \bigwedge_{n=1}^{n_c} [I(n) \rightarrow Gp(j,n)] \tag{2}$$

where n_c is the number of competencies, and $Gp(j,n)$ is the truth value of the assertion "the j employee has a good performance in the n competency". Note that Equation (2) is designed to evaluate the truth value of the assumption that employees will have good performance if the competency is important. This truth value will be reduced only if the employee does not have a good performance in competency i but this competency is important.

Evaluation Predicate 3: Competencies with difficulties

It is important to identify which competency is more difficult to perform or needs more effort for it to be accomplished. To evaluate the truth value that the i competency is a competency with difficulties $D(i)$, the following predicate was settled: "A competency has difficulties if there are some employees that have bad performance in that competency". This is shown in the following expression (3):

$$D(i) = \exists r \neg Gp(r,i) = \bigvee_{r=1}^{l} \neg Gp(r,i) \tag{3}$$

Here, $\vee$ is used to denote the disjuction operator and $\neg$ is used to denote negation. As in previous equations, the same predicate was expressed in two ways. Equation (3) can be read as "i competency will be considered a competency with difficulties if: (a) (First part of the equation) there is at least one employee who does not have a good performance in the i competency "or (b) (Second part of equation) employee 1 does not have a good performance in the i competency OR employee 2 does not have a good performance in the i competency OR so on.

4.2. Discovery of Useful Knowledge for the Human Capital Recruitment Plan

In order to develop an employee recruitment plan for the HRD by using knowledge discovery, the following three actions needs to be evaluated:

Action 1—Determination of the key influential competencies.

Although "the most important competencies" are already defined, usually there are some that lead the others. The above is discovered by the truth value of the predicate $In(i)$: "The i competence is influential". This means that if an employee has a good performance in one influential competence, there are good possibilities of having good performance in the remaining ones. This is shown in the next expression as:

$$In(i) = \forall s\ s \neq i (\forall h\ Gp(h,i) \rightarrow Gp(h,s)) \tag{4}$$

where s is some competence and h is some employee. The influence of some competency could be evaluated by measuring the performance of all the employees in all competencies, therefore Equation (4) would be true if all employees that have good performance in competency i also have good performance in the remaining competencies.

Action 2—Discovery of competencies that are influential in other competencies.

Unlike the previous action, in this one, we try to determine which competencies are influential by a set of other competencies. This is discovered by the truth value of the predicate $In4o(i)$: "The i competence is influenceable for others". This means if an employee has a good performance in a set of competencies, this employee will be good in some competency. This expression can be written as:

$$In4o(i) = \forall l\ (\exists r \in T_i, i \notin T_i |\ Gp(l,r) \to Gp(l,i)) = \bigwedge_{l=1}^{n} \left(\bigvee_{r=1}^{m} Gp(l,r) \to Gp(l,i) \right) \tag{5}$$

where T is a set of competencies, T_i is the set of the competence indexes of T, n is the number of employees, and m is the number of selected competencies. Equation (5) can be read as "*i* competency will be considered a competency influenceable by others if: (a) (First part of the equation) all employees have a good performance in at least one competency within a set of competencies, and a good performance in this *i* competency which is out of the set" or (b) (Second part of equation) employee 1 has a good performance in at least one of the *m* competencies within a set and a good performance in the *i* competency that is out of the set AND employee 2 has a good performance in at least one of the *m* competencies within a set and a good performance in the *i* competency that is out of the set AND so on.

Action 3—Competencies hierarchy to be included in the employee recruitment plan.

Once the competencies have been evaluated, a hierarchization is needed to select the most convenient competencies for the recruitment plan of the HRD. This hierarchization is done by predictive analysis and it is elaborated by the following predicate: "*i* competency hierarchy for its incorporation in the recruitment plan". This means that all the competencies that are important and influential and have some director lacks (competencies with difficulties) should be included in the recruitment plan. This is shown in the next expression as:

$$J(i) = I(i) \wedge In(i) \wedge D(i) \tag{6}$$

where *J(i)* is the final score of the *i* competency. However, Equation (6) could be very constraining. Therefore, a more relaxed condition to evaluate the priority of a competency is used:

$$J(i) = D(i) \wedge (I(i) \vee In(i)). \tag{7}$$

Thus, a competency will be evaluated as a priority if it is important OR influential AND difficult. In this research, the score obtained in Equation (7) is the one used to hierarchize the competencies. Hence, the employee recruitment plan is composed of the highest scored competencies in *J(i)*. Note that, after having the hierarchization of all the competencies, the DM can apply different criteria to choose the most appropriate competencies to be included in the recruitment plan according to the organization goals.

5. Case Study

This study was developed in a local factory that manufactures heavy machine steel pieces. The organization has a traditional HRD with systems and processes for employee training. By following the proposed methodology, the following three principal objectives can be achieved: (a) competencies hierarchy; (b) employees' evaluation; and (c) elaboration of an employee recruitment plan. Before starting with the methodology, the human resources staff focused on finding and describing (according to some internal analysis) the competencies for each of the key positions of the company, which are listed in Appendix A. A management discussion group, including different people from different administrative and operational areas of the company, as well as some general managers and directors, participated in the research. The group of experts created the identification and classification of the talents and competencies that the employees or new candidates should have for the key positions and listed them. For this identification and classification, the experts based their opinions on the book *FYI, a guide for development and coaching* [38]. From the result of this analysis, three competence groups were identified: the first group was made up of 24 competencies related to personal behaviors; the second group consisted of 12 competencies related to motivational aspects; and the third group was made up of 21 competencies that considered professional aspects. To define the groups of competencies necessary to satisfy the needs of the management positions, the application of a survey for all the experts that participated in the study was necessary: 67 persons in total. This survey was designed such that each expert could answer with their own data, perform an auto evaluation, and write down their own experiences and some other information regarding the topic. This research was focused on the management area.

6. Results

After collecting all the information from the applied surveys, it was analyzed, and the following findings were obtained.

6.1. Important Competencies Evaluation

To identify which competencies are the most important according to the experts, the Evaluation Predicate 1 in Equation (1) is evaluated. To do this, a conjunction of all the conditionals associated to each expert was performed using the logic operator AND. A triangular function was settled with the parameters $a = 0$, $b = 10$, and $c = 10$. These parameters were chosen in this way because the evaluation n goes from 1 to 10. Figure 1 shows this triangular function.

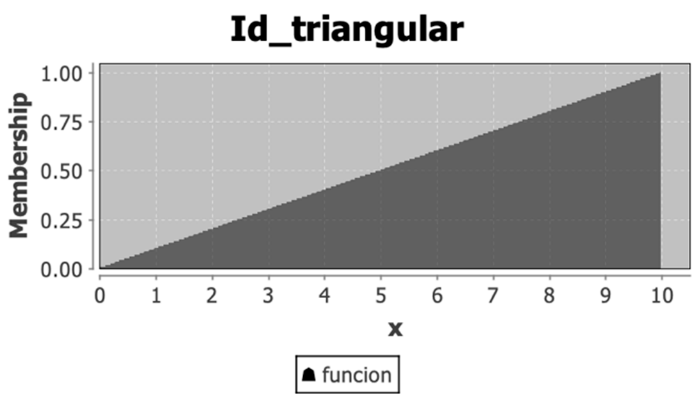

Figure 1. Triangular function for the importance evaluation of competencies.

Similar to Figure 1, another membership function (MF) was created to evaluate if experts considered that competencies were aligned to the organization goals. These MF were then used to determine the importance of each competence.

Remark 1. *After the survey was received, it was found that some people left blank spaces in the answer sheet. In order that the Eureka Universe software could process and analyze the information, those blank spaces were filled with a low value.*

The discovery of useful knowledge from the evaluation of several competencies was then obtained. The collected information from the surveys was useful for evaluating the importance of the different competencies using fuzzy logic with the Eureka Universe interface. Table 1 shows the results from the evaluation process for the total of 52 competencies using the answers of experts.

Table 1 shows the truth value of the 52 competencies according to expert responses. Column C (competence) shows the index of each competency described in Appendix A, and the column Result shows the evaluation for each competency. The table is sorted from the highest to the lowest value in order to visualize the most important competencies for this company. In this case, the most important competencies are: (1) High quality work, ethic and acts based on values; (2) Good communicator, effective, and supports with evidence; and (3) Focused, determined, and persistent.

Table 1. Results of the evaluation of the competencies, using a compound predicate and a linguistic state with a triangular function.

C	Result	C	Result	C	Result
12	0.805	11	0.577	47	0.713
6	0.729	18	0.568	44	0.727
1	0.708	5	0.569	48	0.699
2	0.690	20	0.557	46	0.687
17	0.682	27	0.807	39	0.665
15	0.684	31	0.795	49	0.678
23	0.688	35	0.762	45	0.664
9	0.642	26	0.739	37	0.642
4	0.651	34	0.735	57	0.636
21	0.665	30	0.737	51	0.637
16	0.634	25	0.750	38	0.611
7	0.650	36	0.725	50	0.613
14	0.643	33	0.719	53	0.619
10	0.641	32	0.725	54	0.609
19	0.630	28	0.720	55	0.605
24	0.618	29	0.714	40	0.606
22	0.608	42	0.834	52	0.598
8	0.605	43	0.730		
13	0.589	56	0.734		
3	0.579	41	0.716		

6.2. Personal Evaluation

In this evaluation task, each employee is evaluated according to their own level of compliance of the competencies, e.g., "the j employee has a good performance of all the important competencies". Seven employees were selected by the senior management to evaluate their level of accomplishment for the different competencies. However, on this occasion, because the HRD only wants to focus on management profiles, only administrative skills must be selected. By using the Martha´s Alles methodology [39], 31 out of 52 competencies were selected by the administration, and these competencies are the ones used from now on in the rest of the paper. These competencies are: 1, 2, 6, 9, 10, 12, 14, 15, 17, 22, 25, 26, 27, 28, 30, 31, 33, 34, 35, 36, 37, 38, 41, 42, 43, 44, 46, 47, 48, 49, and 51, which can all be found in Appendix A. The results of the employee's evaluation and the results of the evaluation of competencies (in Equation (1)) were then integrated. Again, triangular MFs were used to model the expert evaluations. The parameter values of these functions were $a = 0$, $b = 1$, and $c = 1$ to evaluate the results of the importance of the competencies, and $a = 0$, $b = 100$, and $c = 100$ to evaluate the good performance of the employee, for all seven employees' evaluations. Thus, the implication regarding the importance of the competence i with the performance of the j employee was evaluated according to Equation (2).

Remark 2. *Note that different values to define the parameters to evaluate fuzzy predicates have been used. This was done to highlight the fact that the values of the parameters are not strict; namely, the scale used by the evaluator can be the one with which he feels more comfortable, e.g., evaluation could be from 1 to 10, 0 to 100, 0 to 1, 1 to 5, etc. This is possible because all the scales map to a value from 0 to 1, which defines the membership degree to the fuzzy MF. Therefore, using the same scale to evaluate all fuzzy predicates, or using a different scale for each evaluation, does not change the results.*

Remark 3. *Unlike previous remark, the use of different MF types will change the results. We encourage the reader to try different MFs, such as sigmoidal or gaussian ones. Let us note that the use of this kind of nonlinear MFs will change the interpretation of the evaluation. For instance, in a linear MF (such as the triangular one) the difference among scores 8, 9, and 10 is the same than the difference among scores 4, 5, and 6; however, if the evaluator does not want to make a big difference* *between a score of 8, 9, or 10 (because a score greater than 8 is good enough), the use of a sigmoidal function could be a good option.*

To integrate all the seven employees with all the 31 competence evaluations, the logic operator AND was used. Table 2 shows the result of the evaluation of the seven employees.

Table 2. Results of the seven leader's evaluation.

Employee	Result
2	0.5377
1	0.5145
3	0.5065
4	0.4975
7	0.4771
5	0.4683
6	0.4599

Table 2 was sorted from the largest to the smallest value, where employee number 2 has the highest true value, with 0.5377, corresponding to their level of satisfaction of the 31 competencies. With this evaluation, it can be noted that there is a similar level of performance among all seven employees.

6.3. Identification of the Competencies with Difficulties

The identification of the competencies that are difficult to perform is done by the evaluation of the predicate in Equation (3). In this case, the information of the performance of the seven employees was used. To integrate all the seven employee evaluations, the logic operator OR was used according to the fuzzy predicate. Table 3 shows the result of the evaluation of the difficulty for each of the 31 competencies. It is observed that all competencies have a truth value equal or less than 0.5, which means that none of the competencies can be considered as difficult to perform.

Table 3. Results of the evaluation of the 31 competencies with their level of importance, influence, and difficulty.

C	Importance	Influential	Difficulty	C	Importance	Influential	Difficulty
1	0.8054	0.8391	0.4103	17	0.7370	0.8359	0.4037
2	0.6829	0.8529	0.4780	18	0.7370	0.8543	0.4936
3	0.6829	0.8391	0.4103	19	0.7195	0.8528	0.4780
4	0.7292	0.8253	0.3462	20	0.7206	0.8647	0.3419
5	0.6841	0.8260	0.3518	21	0.7206	0.8525	0.4780
6	0.7089	0.8573	0.5000	22	0.7508	0.8220	0.3385
7	0.7089	0.8297	0.3663	23	0.7393	0.8451	0.4490
8	0.6424	0.8434	0.4330	24	0.7357	0.8437	0.4330
9	0.6435	0.8345	0.3879	25	0.8349	0.8387	0.4103
10	0.6419	0.8392	0.4103	26	0.6429	0.8253	0.3462
11	0.7959	0.8573	0.5000	27	0.7303	0.8527	0.4780
12	0.7959	0.8253	0.3462	28	0.7161	0.8297	0.3663
13	0.7959	0.8351	0.3943	29	0.6877	0.8253	0.3462
14	0.7629	0.8298	0.3663	30	0.6877	0.8296	0.3663
15	0.7629	0.8437	0.4330	31	0.6115	0.8345	0.3879
16	0.7370	0.8260	0.3518				

6.4. Useful Knowledge Discovery for the Human Capital Recruitment Plan

As mentioned in Section 4, it is important to identify the key competencies that have an influence on others. By doing that, the HRD could focus on special training plans for these competencies. Then, by using the information of the seven employees' performance in all the 31 competencies and by evaluating the relation among them, the truth value of Equation (4) is obtained. In Table 3 is also shown the evaluation of the influence of each of the 31 competencies. It is shown that there is an homogeneous behavior of all the competencies regarding their influence because their influence is very similar, from the most important to the least. This means that all the competencies are strongly related.

On the other hand, with this information, a hierarchization of the competencies can be performed by following Equation (7). This hierarchization will help us to detect all the competencies that are important or influential but with some lack from the experts or directors (competencies with difficulty) and therefore must be included in a recruitment plan. To make the hierarchy of the 31 competencies (the ones related to the management position), all the results regarding the competencies evaluations, influential competencies, and competencies with difficulty, were integrated into a single fuzzy predicate. Figure 2 shows a tree diagram for this evaluation.

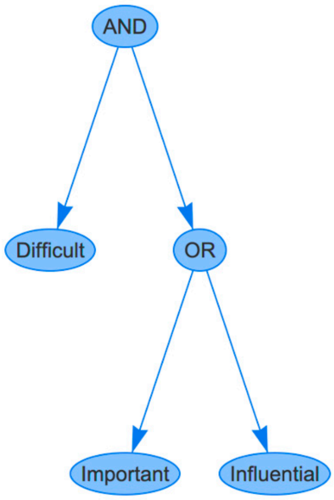

Figure 2. Tree diagram for the identification of the priority of the competencies that are important or influential and have difficulties, from Eureka Universe software.

Table 4 shows the result of the evaluation of the priority of all the 31 competencies. The table is sorted with respect to the priority from the largest to the smallest value. From the result of this evaluation, a criterion to select the competencies that must be included in the recruitment plan was stablished, that is: all the competencies with a priority value above of 0.60 must be included. The first 7 competencies achieve this requirement. Thus, these competencies must be included in the employee recruitment plan:

C2 Practical and good at making decisions;
C6 Good communicator, effective, supports with evidence;
C11 Optimistic;
C18 Accurate, realistic;
C19 Persuasive;
C21 Ability to adapt to change;
C27 Creative, innovative, and visionary.

By comparing Tables 1 and 4, it can be noticed that only competences 2, 6, and 21 are among the first 10, making clear that, in order to have more robust information to make decisions, more than one argument must be considered.

Table 4. Results of the evaluation of the priority of 31 competencies within their level of importance and influential level (sorted by their priority).

C	Importance	Influential	Difficult	Priority	C	Importance	Influential	Difficult	Priority
11	0.796	0.857	0.500	0.644	10	0.642	0.839	0.410	0.558
6	0.709	0.857	0.500	0.631	9	0.644	0.835	0.388	0.542
18	0.737	0.854	0.494	0.630	14	0.763	0.830	0.366	0.541
27	0.730	0.853	0.478	0.619	31	0.612	0.835	0.388	0.538
21	0.721	0.853	0.478	0.617	28	0.716	0.830	0.366	0.535
C19	0.720	0.853	0.478	0.617	7	0.709	0.830	0.366	0.534
2	0.683	0.853	0.478	0.612	30	0.688	0.830	0.366	0.531
23	0.739	0.845	0.449	0.599	12	0.796	0.825	0.346	0.530
15	0.763	0.844	0.433	0.591	16	0.737	0.826	0.352	0.526
24	0.736	0.844	0.433	0.587	20	0.721	0.865	0.342	0.525
25	0.835	0.839	0.410	0.586	4	0.729	0.825	0.346	0.521
1	0.805	0.839	0.410	0.581	5	0.684	0.826	0.352	0.519
8	0.642	0.843	0.433	0.575	22	0.751	0.822	0.339	0.517
13	0.796	0.835	0.394	0.567	29	0.688	0.825	0.346	0.515
17	0.737	0.836	0.404	0.566	26	0.643	0.825	0.346	0.510
3	0.683	0.839	0.410	0.564					

6.5. Employee Recruitment Plan Elaboration (Conclusion about the Priority Evaluation of the Competencies)

The results of this stage must help the HRD of the company to clearly identify which competencies have the priority of being developed in the employees or new recruits, as well as to elaborate better development plans according to the priorities of the evaluated competencies.

For each of the 7 competencies of Table 4 (the ones with a priority bigger than 0.60), useful knowledge was generated. In this case, it is important to discover if there are competencies that have influence on these 7 "key" competencies. Table 5 shows the true value of this assertion for the seven priority competencies. Here (IMP "*" "C27") is the predicate build in Eureka Universe that defines an implication between the antecedent (*) and the consequence (competence 27), i.e., $* \rightarrow C27$, where (*) represents a set of competencies described in the antecedent within Equation (5).

Table 5. Results of the truth value of "being influenced by others" applied to the seven priority competencies to be included in the recruitment plan.

Competence (C)	Truth Value	Compound Predicates
27	0.8777	(IMP "*" "C27")
18	0.8344	(IMP "*" "C18")
21	0.8281	(IMP "*" "C21")
2	0.8011	(IMP "*" "C2")
11	0.7548	(IMP "*" "C11")
19	0.7367	(IMP "*" "C19")
6	0.7100	(IMP "*" "C6")

In Table 5, it is shown that competence 27 has the highest truth value. This means that C27 needs to have a good performance from other competencies. Competences 18, 21, and 2, also have a similar interpretation. A knowledge discovery task was performed to C27 in order to identify which of all competencies were the ones that influenced it the most. After evaluating Equation (5) for C27. It was discovered that competencies 12 and 16 were the ones that influenced it the most. These competencies are:

12 High quality work and ethics, and acts based on values;
16 Self-confident and gains the trust of others.

Figure 3 shows the tree diagram that relates competence 27 with competencies 12 and 16.

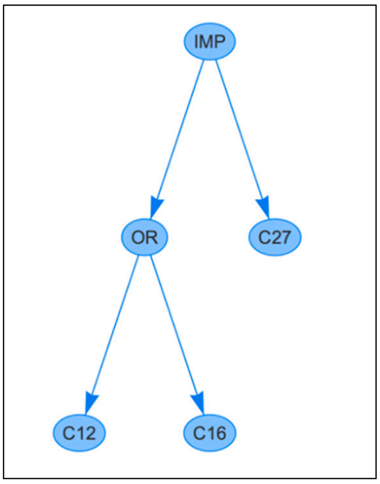

Figure 3. Tree diagram of the result of the truth value of the implication of C27 with C12 or C16, taken from Eureka Universe software.

As mentioned above, it is important to include C27 in the employee recruitment plan of the company. However, it has a truth value of 0.8777 of being influenced by C16 and 12. This means that, in order to better achieve competence 27, the DM must also include competencies 12 and 16 in the employee recruitment plan of the company.

This procedure could also be carried out for the remaining 6 competencies. Nevertheless, in this study, the DM decided to work only with the competencies described above.

7. Conclusions

Human capital is the most important asset for all companies. It is the asset that enables companies to win in the current market conditions if employees of all key departments possess the expected level of abilities and knowledge. In other words, human capital differentiates success from failure. Therefore, all key administrative positions within the company must be occupied by the most qualified and skilled employees. Defining the competence profile required for employees in these key positions is very important, so they can be successful and achieve the best possible results. The use of competence management to assure employees have the optimum abilities and behaviors for the optimal performance of the company is key. Competence management models are enhanced when smart competencies management and business analytics using fuzzy predicates are applied. These enhanced models, together with intentional development plans, help to develop knowledge that can be used to make better decisions. Having a program for the most important competencies will help employees to meet the defined competence profiles to achieve excellent results in different departments of the organization. The proposed method helps us to select the most important competencies and the ones that have more direct influence on them to build the ideal profile for a position. Furthermore, these profiles can be developed and improved by providing information regarding what the most important competence with the highest hierarchy is based on results supported on knowledge discovery. The methodology has benefited from the business analytics by fuzzy predicates approach, which consists of knowledge flow, knowledge engineering, knowledge discovery, and decision-making tasks implemented using the Eureka Universe software. The case study has given us the opportunity of validating the usefulness and viability of the proposed methodology. It provided details concerning the methodology implementation and gave us the opportunity to collect useful experience for further versions of this approach. The use of the proposed methodology in new case studies is recommendable with the same objective. The use of more refined instruments as a starting point associated with each case study is desirable, particularly the use of a 360 degrees approach in the evaluation, which could give a more trustful and useful implementation of this methodology.

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Appendix A. Competency Group for the Research

Id	Behavioral Competencies
1	Focused, determined, and persistent
2	Practical and good at making decisions
3	Flexible, Adaptive, and patient
4	Social, cordial, with skills to motivate people
5	Generalist
6	Good communicator, effective, supports with evidence
7	Self-motivated and enthusiastic
8	Competitive
9	Honest, sincere
10	Responsible and keeps their promises
11	Optimistic
12	High quality work, ethics, and acts based on values
13	Disciplined in their work
14	Creative, uses skills to solve problems
15	Data analysis for making decisions
16	Self-confident and gains the trust of others
17	Focus on quality and towards the client
18	Accurate, realistic
19	Persuasive
20	Cautious
21	Ability to adapt to change
22	Attached to procedures and controls
23	Emotional Intelligence
24	Sense of pertinence

25	Seeks self-realization and fulfillment of personal and work goals
26	Looks for opportunities for professional development and growth
27	Creative, innovative, and visionary
28	Gives more than expected, beyond the job description
29	Interested in conserving natural resources
30	Ability to work on several activities at once and keep important projects moving forward
31	Pushes for results
32	Has an interest in helping others
33	Desire to learn new methods and strategies
34	Appreciate the diversity of cultures at work
35	Ability to work with others
36	Balance between work and private life
Id	Professionals' competencies
37	Functional and technical skills
38	Root Cause Analysis and troubleshooting/8D/Quality Alert
39	Team facilitator and creation of effective teams
40	DMAIC/CPS/Continuous Improvement/Green Belt/Black Belt
41	Negotiation skills
42	Leadership skills
43	Strategic acuity, vision, and purpose management
44	Financial knowledge
45	Acuity in business
46	Conflict management even in ambiguous situations
47	Timely decision making and priority setting
48	Planning and organization
49	Development of direct collaborators and others
50	Political cunning
51	Comfort when interacting with senior executives
52	Concern for others

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