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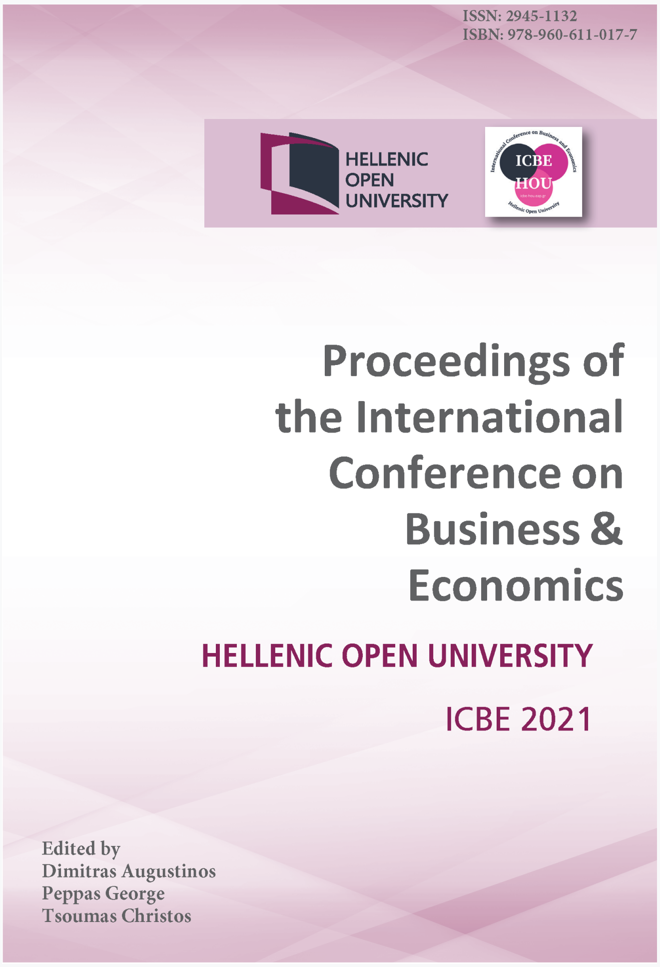

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Human Resources Management Analytics in Private Healthcare Unit

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Abstract

Private Greek healthcare sector consists mainly of medium and small size entities. These entities, especially small ones, rely completely on their Human Resources. However, it seems that they do not avail themselves of new technological methods and tools for assessing their human resources.

The aim of the present study was to create a methodology that will help these entities to evaluate their employees properly and to prove that the empirical knowledge of managers and heads can be enhanced by employing Data Mining methods, in order to create a successful evaluation model.

In the present study, a healthcare unit consisted of 287 employees was selected. Twelve interviews were conducted with 12 managers and heads. A Graphic Rating Scale Table, built by eight qualitative attributes, was given to the interviewees. Those 8 qualitative attributes were combined with 18 quantitative attributes in order for a new model to be created. Data were collected from the Human Resources department. To perform the analysis, Machine Learning methods were used.

This model proved to be functional and capable of giving valid information to management for employees' evaluation. Data Mining methods are quite useful for the HR department and the Administration of the unit.

The above methodology provides low-costs and usable tools, for appropriate employees' evaluation.

EL Classifications: J24, M12, M54, C38.

Key words: Human Resources, Management, Healthcare Unit, Data Mining

1 Introduction

According to Jarvis (2018) human capital is the most vital part of an organization in its effort to gain a competitive advantage. Human Resource Management (HRM) analytics is a field of constant research for practical applications in terms of evaluating its efficiency, effectiveness and contribution to business development (Minbaeva, 2017). During the last 15 years, HRM analytics have been continuously evolving and becoming more and more efficient (Meri, 2016). Data analytics in human resources is based not only on the quantitative cost-benefits analysis, but also on behavioral modeling and analysis of causes and effects (Jac Fitz-enz, 2010) In regards to the evaluation of employees, small and medium enterprises do not possess the basic tools and methods due to their low budget (European Commission, 2019) and their executive's lack of the "evolutionary" thinking (ELSTAT, 2016).

The aim of this study is to point out the ways and methods that directors and heads of a medium private healthcare entity use, in order to manage and evaluate their employees. This knowledge can be rather useful in understanding those methods. Moreover, it aims to discover the most important parameters and characteristics that affect the appropriate functioning and development of the entity. Finally, it aims to create an evaluation method based on the empirical knowledge of the executives and the proposed machine learning model. The effort is focused not only on the experience of the executives but also on quantitative data. Machine Learning methods and particularly data mining processes were used to evaluate the employees and produce the appropriate information for the administration.

Data mining significance lies in the processing of data in order to extract correct and valid information (Kirkos, 2015).

2 Literature review

There are numerous research efforts concerning the management of Human Resources in health units, which mainly describe or analyze processes through theoretical concepts (Marler and Boudreau, 2016). There are few studies linking the relationship between the staff's performance and the performance of small and medium-sized health facilities. (Johnson, 2021).

Employee evaluation which comes directly from their directors and heads provides objective results (Laloumis, 2015). This evaluation can be performed by mathematical models but also by an empirical approach, depending on the data and their importance for the entity's functions (Tavis, 2019). Several methods have been proposed, such as Graphic Rating Scale Table and Behaviorally Anchored Rating Method (BARS) (Pratt, 2020). Interestingly, models that were developed by Data Mining methods (Decision Trees, Random Forest and Neural Network) can be an efficient tool for employees' assessment by the HR departments (Jantan, Hamdan and Othman, 2009). Data mining processes were also used to create patterns that predict employees' retention and satisfaction (Jaffar, and Kanwal, 2019).

It appears that most of researchers that engaged with this subject, made several attempts to create patterns and methods, using exclusively qualitative or quantitative data, without combining them. Thus, the present study attempts to extract information through interviews with the executives and uses this information to create an evaluation model, made by machine learning methods.

3 Sample and Methodology

The entity that was put under the scope is a representative one, in terms of its multifaceted structure, as most of the private healthcare units of that scale. Its' departments consist of specialties that have different responsibilities such as nurses, ambulance crew, salesmen, accounting staff, receptionists, etc. Hence, the evaluation methods must focus on each department, based on their unique attributes.

This study aims to discover the most important attributes that characterize each department and analyze their value in the process of employees' evaluation. The methodology that was followed in order for this model of evaluation to be created, is described in two parts.

3.1 Interviews Analysis Methodology

Interviews were conducted with the directors of the unit and the heads of each department, aiming to their opinion and concerns about their employees. To achieve this goal, 12 interviews were conducted with 12 interviewees (6 heads and 6 directors). The interviews consisted of 13 questions and provided information on how the executives of the unit comprehend issues such as, evaluation of employees, new techniques, recruitment, fees, retention of employees etc.

The inductive methodology was followed for the analysis of the data collected from interviews.

Thematic Analysis (as part of the inductive methodology) was also used. The difference between the productive method and the inductive method is that, the former, is useful in the study when the researcher knows in advance the possible answers of the respondents. In the inductive method, the researcher is guided by the empirical data collected from the interviews (Galanis, 2018). In the productive method the researcher tries to impose his own views on the study. This carries the risk of biased exportation of results. In the inductive method there is no predetermined framework. Of course, the inductive method is time consuming and difficult to analyze, but it produces useful and valid information. Thematic Analysis, as an approach to the inductive method, tries to create thematic units and to codify them through the merging of the answers. (Johansson and Herranen, 2019)

After their completion of the interviews, the results were processed with special tools, in order to extract 6 Thematic Units and evaluate the way used by this entity manage its employees. For thematic analysis we used tools that can help analyze interview data. “NVivo” software was selected. Additionally, “NVivo” software, as a text mining tool, quantifies the participation of executives in each thematic unit based on the duration of the discussion in each question.

There are numerous tools. Some of the most notable were “MAXQDA” and “ATLAS. Ti” (QSR, 2019) which operate similarly. “NVivo” software was rated as the most user-friendly. It is provided as almost full-access software, proving to be quite satisfactory for the research needed in this study (NVIVO, 2019).

3.2 Data mining Analysis Methodology

The Directors and Heads were asked to evaluate their employees based on the adapted Graphic Rating Scale Table that was created. Graphic Rating Scale Table was built in order to draw useful and important qualitative attributes(Pratt, 2020).This Graphic Rating Scale composed of 8 qualitative attributes: *Knowledge & Skills, Team Work, Immediacy, Confidence, Empathy, Communication, Courtesy, and Consistency.*

From a scale of 1 to 5, directors and heads were asked to assess their employees for those attributes. Table 1 presents an example of the Graphic Rating Scale Table, based on this study’s datasets, that was created to evaluate employees of each department. Afterwards, these rates were multiplied with special weighted-values ranging from 1 to 5, depending on the significancy of each attribute. The significancy was based on the knowledge of the directors and heads about the characteristics of their department. The sum of these rates, for each employee, was evaluated in order for heads and directors to decide whether she/he was More Competent or Less Competent. This decision was based on the average rate of each department; each department had its own rating according to the importance of the features selected.

It should be reminded that “More Competent” and “Less Competent” are two evaluation classes that present the skills of the employees based on the above characteristics (it is described further below).

These attributes were combined with quantitative ones in order for a new model to be created.

Table 1. Graphic Rating Table

Id	Department	Consistency X 1	Immediacy X 3	Knowledge&Skills X 5	Courtesy X 2	Confidence X 3	Communication X 1	Empathy X2	TeamWork X4	EvaluationClass
80.984	Employee 1	3	3	5	5	4	3	3	5	More Competent
80.996	Employee 2	2	3	1	3	4	2	2	2	Less Competent
80.983	Employee 3	4	5	3	5	5	3	4	4	More Competent
80.999	Employee 4	2	2	1	3	2	3	2	4	Less Competent
80.866	Employee 5	5	4	4	4	3	2	3	4	More Competent
80.962	Employee 6	4	5	3	5	5	3	4	4	More Competent
80.967	Employee 7	5	4	4	4	3	2	3	4	Less Competent

Before the interview conduction, data were collected from the HR department, regarding age, working experience and salary, absence of work, working days etc. Consent was granted by the head of the healthcare unit and all the employees were informed. There was no objection for sharing this information. Specialized indicators were also collected and used, from institutes such as APQC (APQC, 2019) and Digital HR Academy AIHR (AIHR, 2018).

After these procedures, 26 attributes (Table 2) were used for the Data mining processes on a 287 employees dataset. These attributes (Variables) were the *Indepented Variables.* The variable used to show how each employee was evaluated was the *Depented Variable* or *Class Variable.* In this case, the depented variable may have one of two alternative class values. The methodology that was selected was the *Classification Method*. This method is part of *Supervised Learning,* with which was assessed the impact of the independent variables on the dependent variable (Kirkos, 2015).

In this study, the *Depented Variable* consists of two class values, i.e. the “More Competent”class value and the “Less Competent” class value. Sadly, the first evaluation that was performed revealed a setback. The first data that were extracted, showed that the *Depented Variable* was devided on 213 employees classified as “More Competent” and 74 as “Less Competent”, which creates an inballanced dataset. According to Chawla et al (2002), large range between the two components is a predicament, as “*the cost of misclassifying an abnormal (interesting) example as a normal example is often much higher than the cost of the reverse error”* (Chawla, Bowyer, Hall and Kegelmeyer, 2002).

The high rate in the ‘More Competent” class allows error rate, favoring the majority class. In order to overcome this obstacle, a filter called Synthetic Minority Oversampling Technicue (SMOTE) was applied. SMOTE managed to balance the variable class categories and to significantly reduce classification errors SMOTE is a filter supervised method (Witten, Frank and Pal, 2016).

Table2. Evaluation Attributes (Variables)

No	Independent Variables (Attributes)	No	Independent Variables (Attributes)
1	Age	14	Working days
2	Years of Experience	15	Absences Cost
3	Sex	16	Labor Cost
4	Absence	17	Participation in Profits
5	Absences to Total Working Days	18	Participation in Total Expenses
6	Knowledge & Skills	19	Participation in Total Profits
7	Immediacy	20	Overtime, Nocturnal, Holidays
8	Confidence	21	Working Days to Labor costs
9	Empathy	22	Experience to Income
10	Communication	23	Experience to Cost
11	Courtesy	24	Experience to Profit
12	Consistency	25	Absences to Total Absences
13	Team Work	26	Absences to Cost
Dependent Variable			
“Evaluation” variable with 2 classes: “More Competent” and **“**Less Competent”			

To carry out the analysis and to export an evaluation model, tools from WEKA software were used. This software was developed by Waikato University in New Zealand (Waikato, 2016).

This software could be described as a complete toolbox with an easy-to-access interface. The user can relatively easily compare and choose the appropriate methods for each study.

Pre-process

The Database divided initially in two datasets. The first dataset consists of the department of Sales, Management, Customer Information and Accounting. The second dataset consists of the department of Nurses, Ambulance crew, Microbiological laboratory technologists, Radiological machine operators, and customer service, Cleaners, Conservators and Security.This separation was made with criterion that the departments of the first dataset have diferent kind of tasks from the departments of the second dataset. As a result, the distinquished characteristics of each department create the need of a different approach.

SMOTE was applied to all datasets in order to balance variable class categories (Chawla, Bowyer, Hall and Kegelmeyer, 2002). For example the evaluation procedure of the first dataset categorized 66 employees as "More Competent" and 12 as "Less Competent". With the SMOTE filter applied to balance the evaluation values, an equilibrium was achieved, with 66 employees classified as "More Competent" and 66 as "Less Competent". Same procedure was used to balance the evaluation values of second dataset and of each department separately.

Classification

The final step was to apply the classification algorithms. The classifiers used for model construction were Random Forest and Neural Networks. Random Forest belongs to tree classifiers. Tree classifiers start by a selected attribute that is called "root" and, through "nodes", it produces rules. These rules assess the class values and produce the evaluation result. Random Forest is a random combination vector of different roots, independently sampled (Breiman, 2001).Neural Networks is a classifier that simulates brain functions and is used by neurobiological mathematics. It is a network constructed from connected layers (Vellido, Lisboa, Vaughan, 1999). Their ability to predict the class of unknown observations proved to be quite handy in this kind of studies (Kirkos,2015). For the evaluation model that was studied herein (classification and prediction of dependent variable categories), the feed forward multilayer perceptron (MLP) network was applied. This is a classifier that uses the back propagation (BP) algorithm to train a multi-layer perceptron to classify each case reducing the errors to minimum (Raman, Smriti, Rajat, 2020).

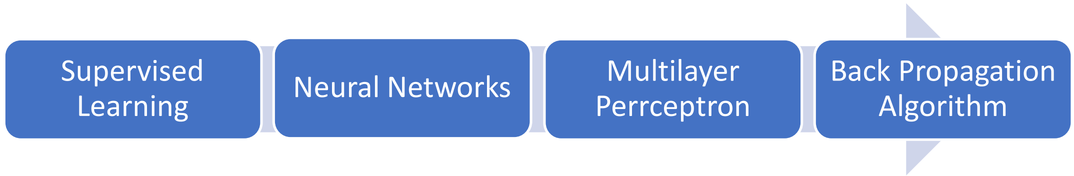


Figure1. Neural Networks Processes (followed in study)

Cross validation with the “10 folds” WEKA method was performed to validate the model ability to classify unknown observations. This method creates 10 subsets from the initial dataset. In an iterative procedure, nine subsets are used for training and the tenth subset is used for validation (Kirkos, 2015).

“ClassifierAttributeEval” and “Ranker” were used to classify the most important attributes on the assessment of employees. ClassifierAttributeEval” is an attribute selection method that evaluates the worth of an attribute by using a user–specified classifier. In this study Random Forest and Neural Networks are the evaluators. “Ranker” is an attribute selection method that ranks attributes by their individual evaluations (Witten, Frank and Pal, 2016). These classification proccesses were used in all of this study’s models in order to evaluate the employees of each department. The software used in this work is *WEKA3.8.3* (Waikato, 2016). This software is designed to use tested methods in new datasets. It also includes data preparation, pre-processing, evaluation processes, validation processes and attributes selection processes. Finally, it measures the accuracy of a model against unknown observations, exporting presentable patterns (Kirkos,2015).

4 Results

Part1

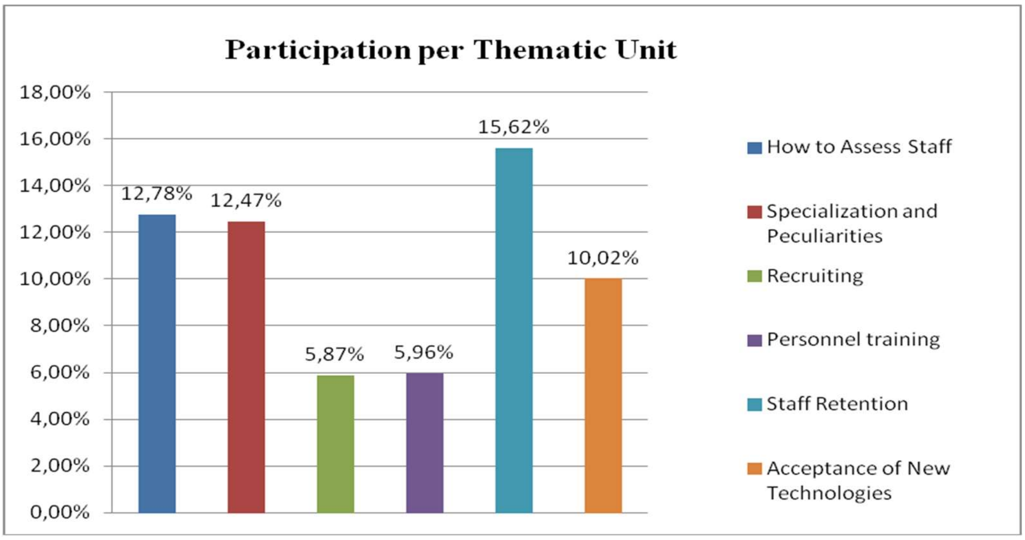
Interview Analysis Results

The following thematic units were produced by the interviewing process.

1. Staff Assessment: How directors and heads evaluate their staff.
2. Specialization and Peculiarities: This unit is about the unique characteristics that the executives consider regarding their departments.
3. Recruiting: This thematic unit is about the main characteristics regarding the process of recruiting staff of each department.

4. Personnel training: This unit assesses directors' and heads' opinions about their staff's training programs. To be more specific, the goal was to understand the employees' development efforts per department.
5. Staff Retention: The aim of this thematic unit was to evaluate how directors and heads manage to retain talented employees in the entity.
6. Acceptance of New Technologies: The aim was to evaluatethe executives' consideration of using new technological tools for assisting their empirical knowledge.

The participation of each director and head on each Thematic Unit was the measurement criterion for the significancy of each unit (Graph 1).



Graph 1.Participation (%) per Thematic Unit

The highest rate was observed for "Staff Retention" thematic unit (15.60%). The second largest participation was about "Staff assessment" (12.80%). "Specialization and Peculiarities" unit was third (12.47%) and discussions in this thematic unit help to choose the most important qualitative attributes (variables). Thematic unit "Acceptance of New Technologies" was next with (10.02%). It is encouraging that most directors and heads (60%) found the technological tools for evaluation of the staff, quite useful. Despite their awareness of these applications, so far, no one had included them on their workplace tasks. Twenty four percent of the directors and heads appeared to believe that evaluation of the staff should be done through the contact of the executives with employees and by using technological means. The "Personnel Training" thematic unit was fifth (5.96%). The sixth and last in participation was the "Recruiting" (5.87%).

Part2

Data mining Analysis Results

As mentioned in pre-process procedure, dataset was divided in two individual parts based on each department's duties. These parts include a variety of relevant departments. For each dataset, one department was analyzed further in order to evaluate properly the model's efficiency. The chosen departments manage different kind of tasks and number of employees. Hence, four analyses were performed. One analysis was about the first dataset, followed by a specific analysis regarding with the department of "Sales" that belongs in the first dataset. "Sales" were chosen as the representative department. The third analysis was about the second dataset, followed by the final specific analysis regarding with the department of "Ambulance crew' that belongs in the second dataset (the representative analysis). The aim was to present, whether or not the model is effective, in order to discover significant attributes for evaluation purposes.

Applying Data mining processes to the first dataset

The first dataset includes the departments of "Sales", "Management", "Customer Information" and "Accounting". As mentioned in pre-process, directors and heads classified 66 employees as "More Competent" and 12 as "Less Competent".

With SMOTE filter applied to balance the evaluation classes, an equilibrium was achieved, with 66 employees classified as "More Competent" and 66 as "Less Competent". The results of the classification proccess (Table 3) presents the accuracy rate of each classifier.

Table3. Classification Accuracy Rate

Model	Neural Networks	Rate	Random Forest	Rate
Correctly Classified Instances	108	81.82%	121	91.67%
Incorrectly Classified Instances	24	18.18%	11	8.33%
Total Classified Instances	132	100.00%	132	100.00%

Neural Networks achieved 81.82% classification accuracy, comparatively to Random Forest that achieved 91.67%, which is a very good classification rate.

Confusion Matrix visualizes the accuracy of a classifier by comparing the actual and predicted classes. Table 4 and Table 5, presents the results of Neural Networks and Random Forest classification accuracy.

Table 4. Classified Instances with Neural Networks

	a	b	Classification
Classified as:	59	7	a =LessCompetent
	17	49	b = MoreCompetent

It appears that Neural Networks with the "Less Competent" class managed to correctly classify 59 employees as "Less Competent", while 7 employees were erroneously classified as "More Competent". In regards with the "More Competent" class, 17 employees were erroneously classified as "Less Competent", while 49 were correctly observed as "More Competent".

Random Forest's "Less Competent" class analysis, classified correctly 60 employees as "Less Competent" and, erroneously, 6 employees as "More Competent". The "More Competent" class produced 5 employees incorrectly as "Less Competent", while 61 were correctly classified as "More Competent".

Table 5. Classified Instances with Random Forest

	a	b	Classification
Classified as:	60	6	a =Less Competent
	5	61	b = More Competent

From the classification accuracy rate table (Table 3), Random Forest classifier was accurate at a proportion of 91.67% of the observations (employees). In comparison to Neural Networks results (Tables 4 and 5), Random Forest managed to minimize the classification error that was produced on the "More Competent" class.

Results showed that Random Forest is the proper tool for ranking the most important attributes on the assessment of employees.

Table6. Attributes Significance ranking table

Methods: "Random Forest", "ClassifierAttributeEval","Ranker"					
No	Attribute (Variable)	Significance Index	No	Attribute (Variable)	Significance Index
1	**Courtesy**	**0.2924**	14	**Sex**	**0.1879**
2	**Communication**	**0.2864**	15	**Participation in**	**0.1879**
3	**Knowledge & Skills**	**0.2697**	16	**Labor Cost**	**0.1742**
4	**Absences to Total**	**0.2697**	17	**Trust**	**0.1742**
5	**Immediacy**	**0.2500**	18	**Experience to Income**	**0.1697**
6	**Absences to Cost**	**0.2348**	19	**Absences Cost**	**0.1515**
7	**Trust**	**0.2152**	20	**Participation in Total**	**0.1318**
8	**Working Days to Labor costs**	**0.2091**	21	**Experience to Profit**	**0.1250**
9	**Team Work**	**0.2091**	22	**Empathy**	**0.1197**
10	**Absences to Working Days**	**0.2061**	23	**Years of Experience**	**0.1174**
11	**Absence**	**0.2030**	24	**Age**	**0.1136**
12	**Consistency**	**0.1970**	25	**Experience to Cost**	**0.1030**
13	**Working Days**	**0.1955**	26	**Overtime, Nocturnal, Holidays**	**0.0682**

"Attributes significance ranking table" (Table 6), presents the results on 26 variables rated by the "ClassifierAttributeEval" via Random Forest classifier.

Qualitative attributes (Courtesy, Communication, Knowledge & Skills) presented the highest rate (Table 6).

These were the same attributes that managers and heads used to evaluate their staff. "Absences to Total Absences" and "Absences to Cost" were the next important indicators, followed by "Working Days to Labor costs" and "Absences to Working Days", concerning financial issues. In fifth and ninth position were qualitative attributes again.

It was ascertained that evaluation model uses both of qualitative and quantitative data for evaluation of employees.

Applying Data mining processes to the “Sales” dataset

At this point, our study attempts to discover the most important attributes for the evaluation of "Sales" department employees. Directors and Heads assessed them and 27 were evaluated as “More Competent”, while 7 as "Less Competent".

SMOTE filter equalizes these classes, with 27 as “More Competent” and 24 as "Less Competent ". Below is presented the classification accuracy of each classifier.

Table7. Classification Accuracy Share

Model	**Neural Networks**	**Share**	**Random Forest**	**Share**
Correctly Classified Instances	34	66.67%	43	84.31%
Incorrectly Classified Instances	17	33.33%	8	15.69%
Total Classified Instances	51	100.00%	51	100.00%

Neural Networks achieved 66.67% classification accuracy and Random Forest achieved 84.31%.

Among these two classifiers, Random Forest is the most accurate. Neural Networks “Confusion matrix” and Random Forest “Confusion matrix”, are presented below.

Table 8. Classified Instances with Neural Networks

Classified as:	**a**	**b**	**Classification**
	18	6	a =Less Competent
	11	16	b = More Competent

Regarding the “Less Competent” class, it was revealed that Neural Networks managed to classify correctly 18 employees as “Less Competent”, while 6 employees were incorrectly classified as “More Competent”. The “More Competent” class classified incorrectly 11 employees as “Less Competent” and 16 correctly, as “More Competent”.

Table 9. Classified Instances with Random Forest

Classified as:	**a**	**b**	**Classification**
	20	4	a =Less Competent
	4	23	b = More Competent

Random Forest, classifies 20 employees as “Less Competent” and 23 as “More Competent”, correctly.

Hence, Random Forest was applied to the “Attributes significance ranking tables”.

Table 10. Attributes Significance ranking table

Methods: “Random Forest”**,** “ClassifierAttributeEval”,”Ranker”					
No	Attribute (Variable)	Significance Index	No	Attribute (Variable)	Significance Index
1	**Absences to Working Days**	**0.2392**	14	**Participation in Total Cost**	**0.1059**
2	**Courtesy**	**0.2196**	15	**Working Days**	**0.1020**
3	**Communication**	**0.2039**	16	**Labor Cost**	**0.0980**
4	**Team Work**	**0.2039**	17	**Knowledge & Skills**	**0.0980**
5	**Immediacy**	**0.1765**	18	**Participation in Profits**	**0.0902**
6	**Sex**	**0.1765**	19	**Empathy**	**0.0863**
7	**Participation in Total**	**0.1686**	20	**Absence to Total**	**0.0706**
8	**Working Days to Labor cost**	**0.1529**	21	**Overtime, Nocturnal, Holidays**	**0.0001**
9	**Absence to Cost**	**0.1529**	22	**Years of Experience**	**0.0001**
10	**Absence**	**0.1412**	23	**Experience to Income**	**0.0001**
11	**Absences Cost**	**01216**	24	**Experience to Profit**	**0.0001**
12	**Trust**	**01137**	25	**Experience to Cost**	**0.0001**
13	**Consistency**	**0.1137**	26	**Age**	**0.0001**

The indicator “Absences to Working Days” displays the highest rate, followed by four qualitative attributes and six quantitative attributes (Table 10).

This analysis revealed that this model deploys both qualitative and quantitative data for employees’ evaluation process.

Applying Data mining processes to the second dataset

On the evaluation procedure of the second dataset, participated seven departments; Nurses, Ambulance crew, Microbiological laboratory technologists, Radiological machine operators, Customer service, Cleaners, Conservators and Security.

These departments count a total of 209 employees. Directors and Heads assessed 147employees as “More Competent” and 62 as "Less Competent

Due to the imbalance of the categories, SMOTE filter was applied in order to achieve equilibrium. Class equilibrium achieved, with 142 employees classified as "Less Competent" and 147 as “More Competent”.

Table 11. Classification Accuracy Share

Model	**Neural Networks**	**Share**	**Random Forest**	**Share**
Correctly Classified Instances	185	64.01%	231	79.93%
Incorrectly Classified Instances	104	35.99%	58	20.,07%
Total Classified Instances	289	100.00%	289	100.00%

Neural Networks reached classification accuracy of 64.01%, while Random Forest achieved a proportion of 79.93%. These results were significantly reduced compared to the first dataset’s observations. The Random Forest rate was satisfying.

Confusion matrix applied with Neural Networks and Random Forest as it follows (Tables 12 and 13).

Table 12. Classified Instances with Neural Networks

	a	**b**	**Classification**
Classified as:	89	53	a =LessCompetent
	51	96	b = MoreCompetent

Neural Networks with the “Less Competent” class managed to classify correctly 89 employees as “Less Competent” and 53 employees incorrectly, as “More Competent”. The “More Competent” class classified 51 employees incorrectly as “Less Competent” and 96 correctly, as “More Competent”.

Table13. Classified Instances with Random Forest

	a	b	Classification
Classified as:	112	30	a =LessCompetent
	28	119	b = MoreCompetent

Random Forest, classifies 112 employees as "Less Competent" and 119 as "More Competent", correctly.

Random Forest, compared to Neural Networks in "Confusion Matrix" results, managed to minimize classification error with both classes. Hence, it is the most efficient classifier for this dataset.

The "Attributes Significance ranking table" presents the results of 26 variables that were rated by the "ClassifierAttributeEval" and classified with Random Forest.

Table 14. Attributes Significance ranking table

Methods: "Random Forest", "ClassifierAttributeEval","Ranker"					
No	Attribute (Variable)	Significance Index	No	Attribute (Variable)	Significance Index
1	**Team Work**	**0.2076**	14	**Participation in Total**	**0.0900**
2	**Courtesy**	**0.1661**	15	**Experience to Income**	**0.0858**
3	**Consistency**	**0.1644**	16	**Experience to Cost**	**0.0857**
4	**Communication**	**0.1557**	17	**Absences to Working**	**0.0810**
5	**Trust**	**0.1556**	18	**Participation in Total**	**0.0761**
6	**Knowledge & Skills**	**0.1552**	19	**Sex**	**0.0720**
7	**Empathy**	**0.1419**	20	**Absences Cost**	**0.0657**
8	**Absence to Total Absence**	**0.1308**	21	**Absences to Cost**	**0.0656**
9	**Participation in Profits**	**0.1280**	22	**Working days**	**0.0609**
10	**Labor Cost**	**0.1159**	23	**Experience to Profit**	**0.0567**
11	**Overtime, Nocturnal, Holidays**	**0.1093**	24	**Years of Experience**	**0.0294**
12	**Absence**	**0.1017**	25	**Immediacy**	**0.0221**
13	**Working Days to Labor**	**0.0976**	26	**Age**	**0.0001**

Qualitative attributes as Team Work, Courtesy, Consistency, Communication, Trust, Knowledge & Skills and Empathy present the highest rate (Table 14). Apparently, that model rated the empirical knowledge of Directors and Heads as the most important attributes for assessing employees, followed by quantitative attributes that could be equally useful.

Applying Data mining processes to the "Ambulance Crew" dataset

In this last procedure, the department of "Ambulance crew" was evaluated. Directors and Heads assessed 43 employees as "More Competent" and 26 employees as "Less Competent". Due to the imbalance of the categories, SMOTE filter was used and 42 observations were characterized as "Less Competent" and 43 as "More Competent".

At this balance of instances, classifiers achieved their optimum classification accuracy. Table 15 presents the classification accuracy of each classifier.

Table 15. Classification Accuracy Share

Model	**Neural Networks**	**Share**	**Random Forest**	**Share**
Correctly Classified Instances	60	70.59%	50	58.82%
Incorrectly Classified Instances	25	29.41%	35	41.18%
Total Classified Instances	85	100.00%	85	100.00%

Neural Networks achieved better classification accuracy, with a proportion of 70.59%, compared to Random Forest that achieved 58.82%.

The Confusion matrix was applied with Neural Networks and Random Forest.

Table 16. Classified Instances with Neural Networks

	a	**b**	**Classification**
Classified as:	29	13	a =Less Competent
	12	31	b = More Competent

Neural Networks classified 29 employees as "Less Competent" and 31 as "More Competent", correctly.

Table 17 Classified Instances with Random Forest

Classified as:	**a**	**b**	**Classification**

	26	16	a =Less Competent
	19	24	b = More Competent

Random Forest managed to classify 26 employees as “Less Competent” correctly and 24 as “More Competent” correctly.

Neural Networks, compared to Random Forest in “Confusion Matrix” results, managed to minimize classification error with both classes. Hence, it is the most efficient classifier for this dataset.

The “Attributes Significance ranking table” presents the results of 26 variables that were rated by the “ClassifierAttributeEval” and classified with Neural Networks.

Table 18 Attributes Significance ranking table

Methods: “Random Forest”**,** “ClassifierAttributeEval”,”Ranker”					
No	Attribute (Variable)	Significance Index	No	Attribute (Variable)	Significance Index
1	**Age**	**0.1482**	14	**Participation in Total**	**0.5647**
2	**Overtime, Nocturnal, Holidays**	**0.1152**	15	**Working days**	**0.5176**
3	**Absences to Cost**	**0.0965**	16	**Team Work**	**0.4471**
4	**Courtesy**	**0.9413**	17	**Empathy**	**0.4235**
5	**Experience to Profit**	**0.9412**	18	**Absences**	**0.3059**
6	**Experience to Income**	**0.9176**	19	**Communication**	**0.2824**
7	**Years of Experience**	**0.8941**	20	**Sex**	**0.1882**
8	**Experience to Cost**	**0.8706**	21	**Absences to Total**	**0.1647**
9	**Absences Cost**	**0.7765**	22	**Absences to Working**	**0.1176**
10	**Participation in Total**	**0.7529**	23	**Immediacy**	**0.0706**
11	**Working Days to Labor**	**0.6588**	24	**Knowledge & Skills**	**0.0001**
12	**Participation in Incomes**	**0.6587**	25	**Consistency**	**0.0001**
13	**Labor Cost**	**0.6353**	26	**Trust**	**0.0001**

Quantitative attributes were classified as most significant for the evaluation of the “Ambulance Crew” department employees. “Age” was classified as the most important attribute, followed by “Overtime, Nocturnal, Holidays”, “Absence to Cost” and then, thought-provokingly, the qualitative attribute “Courtesy”. This model evaluates “Ambulance Crew” department employees by giving priority to quantitative attributes.

5 Conclusions

The aim of this study was to create an employees’ evaluation model using qualitative data, mingled with data extracted from HR department archives. The qualitive data derived from the empirical knowledge of directors and heads of a Private health care Unit. The goal was to discover the most important characteristics that HR management can use in order to evaluate their employees. Data analysis proceeded with interview-analysis techniques and machine-learning techniques. Conclusively, a successful and functional employees’ evaluation model was built, based on a specific entity, operating in Greece’s private health sector.

Interviews

The interviews with the executives initially provided information on the characteristics of each department and the specialization required of their employees. This information provided the weighed quality variables (Table 1), selected for the evaluation of employees by the directors and heads of each department. Moreover, interviews provided data about the current way of staff evaluation, the executives’ acceptability of technological methods, the staff retention and how new employees were selected.

The purpose of the above analysis was to comprehend the way that this specific entity manages their employees. This information distinguished the most significant attributes depending on the culture of this entity, combined with the indicators and values that matter the most for them.

Data Mining Model

Taking into consideration the directors' opinion and conclusions, the study was led to the selection of the 8 qualitative variables (Table 1). The generated model consisted of a qualitative and quantitative characteristics mixture. The hypothesis was that the participation of both types of characteristics should be employed for the evaluation of employees. In order to assay the hypothesis, this data was mingled with the quantitative values resulted from HR Department, and produce the final 26 variables. Afterwards, the total number of employees in the unit (287 employees) was divided into two data subsets, in order for the results to be obtained homogeneously. The “first dataset” consisted of management and administration departments, with 78 employees. The “second dataset” consisted of departments that are responsible for the services provided to customers. From the two sets of data, a representative department was selected; the “sales” subset was chosen from the first dataset (34 employees) and the “Ambulance Crew” subset was chosen from the second dataset (67 employees). This selection was made because the model had to be tested on individual departments as well. Table 19 presents in summary the classification accuracy of each model that was created from the aforementioned datasets.

Table 19. Summary Classification Accuracy Table

Dataset	First Dataset	Sales	Second Dataset	Ambulance Crew
Classifier	**Random Forest**	**Random Forest**	**Random Forest**	**Neural Networks**
Correctly Classified Instances	91.67%	84.31%	79.93%	70.59%
Incorrectly Classified Instances	8.33%	15.69%	20.,07%	29.41%
	100.00%	100.00%	100.00%	100.00%

The model’s accuracy in all datasets is quite satisfactory, as it manages to correctly classify a range from 71% to 92% of the observations. That led to the conclusion that the attributes selected from this model were accurate for the employees’ evaluation.

The results show that a functional model based on each entity’s attributes, can be quite competent on giving valuable information to the management about its employees. Random Forest and Neural Networks Classifiers managed to mix successfully the qualitative and quantitative attributes. Additionally, these classifiers ranked the variables’ significancy in order to produce valid information that management departments could benefit for their staff’s evaluation process. The model that was created improves the initial position and produces a functional empirical and scientific evaluation “mixture”.

Strengths, Limitations and Future Extensions

The model that was developed herein was based on the data collected from a specific entity that operates in the Greek Health Sector. In order to develop a similar model in other entities too, analysts must understand the “culture” and attributes of the entity that they aim to study. This research presents new perspectives for the HR department of organizations that operate in health sector. The above methodology provides low-costs and relatively easy processed tools, for appropriate employees’ evaluation. Additionally, Machine Learning methods proved to be quite useful for HR department and the Administration of the unit.

Similar models could be developed for other responsibility areas of HR departments, e.g., finding new executives or employees and organizing training programs.

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