An Evaluation Model for Dynamic Motivational Analysis

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Abstract: In the past decades, a significant number of researches have sought to determine which factors make a worker satisfied and productive. Currently, there are intensive efforts to develop efficient systems for motivational analysis and performance evaluation. Current approaches of measuring motivation are very focused on questionnaires and periodic interviews. These periods are most often greater than 6 months, and in most cases performed annually. With today's communication dynamics, employees can be influenced at any time by external factors of market supply and demand, as well as communications with peers and colleagues in the device mesh. It is becoming increasingly important to obtain real-time information to take preventive or corrective measures in a timely manner. This paper proposes a framework for real-time motivational analysis using artificial intelligence techniques in order to evaluate employee' motivation at work. The motivation is evaluated from different groups of indicators: a static and periodic group (interviews and questionnaires), and two other dynamic groups that collect information in real time. With the results generated by the system, it is possible to make important decisions, such as understanding the emotional interactions among employees, improving working conditions, identifying indicators of dissatisfaction and lack of motivation, encouraging promotions, salary adjustments and other situations.

1 INTRODUCTION

Organizational motivation is a continuous field of research, given its professional, technical and personal relevance. There are several criteria that influence the motivation of employees, including relations with the leader, working conditions, safety, personal life, recognition, professional growth, salary, and benefits. In order to evaluate such criteria, it is necessary and appropriate to provide a heterogeneous structure adapted to different motivational dimensions.

In the past decades, a significant number of researches have sought to determine which factors make a worker satisfied and productive, as opposed to those factors that lead to dissatisfaction and poor performance (Tay and Diener, 2011; Matei and Abrudan, 2016; Alharthi et al., 2017). The two most prominent authors in this subject are Frederick Herzberg and Abraham Maslow. Maslow published the hierarchy of needs (Maslow, 1943), while Herzberg developed the theory of the two factors - hygienic and motivational (Herzberg, 1971). Motivation is the best potential source of increased productivity. Thus, employee capabilities will be best used, leading to job satisfaction and improved productivity.

Efforts have been made to identify motivational factors or sentiments based on the support of Artificial Intelligence (AI) techniques (Toy, 2014, Medhat, Hassan and Korashy, 2014, Chumkamon, Masato and Hayashi, 2015), but they are not enough to provide effective solutions to this matter. Developers of AI systems turn to the capability of researchers in achieving goals, performing tasks or solving problems. This is perhaps more meaningful than the motivational aspects of the systems (Kelley and Waser, 2018).

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interviews. These periods are most often greater than 6 months, and in most cases performed annually. With today's communication dynamics, employees can be influenced at any time by external factors of market supply and demand, as well as communications with peers and colleagues in the device mesh. It is becoming increasingly important to obtain real-time information to take preventive or corrective measures in a timely manner. On the other hand, interview responses and questionnaires do not always faithfully reflect the degree of satisfaction or dissatisfaction of employees, who often prefer not to expose their real sentiments.

This paper proposes a conceptual framework for real-time motivational analysis using artificial intelligence techniques in order to evaluate employee' motivation at work. The motivation is evaluated from different groups of indicators: a static and periodic group (interviews and questionnaires), and two other dynamic groups that collect information in real time.

2 RELATED WORKS

We reviewed the literature related motivational analysis using artificial intelligence techniques, especially the analysis of sentiments and natural language processing. We found four scientific articles which deserve to be highlighted.

The first one presented by Tay and Diner (2011) analyses a sample from 123 countries. It evaluates the correlation between the fulfilment of necessities (Maslow, Deci and Ryan, Ryff and Keyes theories) and subjective well-being, including life assessment of positive and negative sentiments. Within the various cultures studied, using statistical analysis and regression techniques, they found that the attendance of the psychosocial needs is adherent to the conditions of the country. On the other hand, fulfilment of basic and security needs is not associated with the conditions of the country.

The second article described by Akdemir and Arslan (2013) focused to measure of teacher motivation. For this, they constructed a set of 51 attributes based on the motivational and hygienic factors of Herzberg. These attributes were evaluated using a five-point scale (none, small, moderate, very, and completely). In addition, as a pilot test, the scale was applied to 150 teachers from different areas of Zonguldak Province, Turkey. In order to evaluate the data, the authors used factorial analysis, correlation tests, and data normalization. The results indicated a reliable and valid motivational scale that can be used to measure teacher motivation in four dimensions: communication, professional growth, institutional progress and expectations.

In the study published by Medhat, Hassan and Korashy (2014), the objective was to provide an overview on algorithms and applications used for the analysis of sentiments. These was described in 54 recently published articles (2010 to 2013) on this subject. The authors emphasize that the sentiment classification algorithms and features selection techniques are still research fields to be explored. On the other hand, Naive Bayes and Support Vector Machines are Machine Learning approach algorithms most frequently used to solve problems related to sentiment classification. The main source is the lexicon WordNet which is available in several languages besides English.

In the Ravi and Ravi (2015) paper, the authors worked on opinion mining in 160 papers published between 2002 and 2015. They used approaches and applications commonly required for the analysis of sentiments. The research is organized based on sub-tasks to be performed, machine learning and natural language processing techniques. In the literature review carried out by the authors, seven dimensions were analysed: subjective classification, sentiment classification, measurement review utility, lexical creation, opinion word and aspect of product extraction, opinion spam detection and several opinion mining applications. In addition, the identified approaches involved lexical-based machine learning, hybrid approaches, ontologies-based approaches and non-ontologies (considered for lexical creation and feature extraction).

Considering the above, it was noticed that the studies analysed aspects related to motivational analysis from artificial intelligence techniques, especially analysis of sentiments and natural language (Akdemir and Arslan 2013, Ravi and Ravi 2015). However, it should be noted that the study by Ravi and Ravi (2015) deals with a bibliographic review, whereas the study by Akdemir and Arslan (2013) uses an approach to analyse the motivation of teachers in the academic context.

3 PROPOSED APPROACH

In this study we sought to analyse motivation in the business context. Our approach considers, besides the commonly used questionnaires, different sources to obtain information related to motivation of the employees.

In order to obtain the indicators of motivation, the main source was Herzberg's two-factor theory and a brief description of the indicators used in the theory. Next, we present the data sources used to input the quantitative and qualitative values of the indicators. These data sources include the traditional 360-degree evaluation questionnaires, data obtained from the Human Resources transactional systems, external information about the job market, and the main data sources accessed to obtain the information to perform the sentiment analysis.

3.1 Herzberg's Two-factor Theory Indicators

As previously cited, this theory postulates that there are two groups of factors: hygienic factors and motivational factors. The first group (extrinsic) is formed by external elements capable of influencing people's dissatisfaction but does not guarantee satisfaction. The second group (intrinsic) elevates the self-image about the capacity for achievement, thus promoting motivation.

Absence of hygienic factors creates dissatisfaction, but their presence will not necessarily create satisfaction. On the other hand, absence of motivator factors does not imply dissatisfaction, but their presence will create satisfaction (Shen and Yu, 2009). Therefore, the two-factor theory considers that the presence of motivation factors will lead to satisfaction, while hygienic factors should avoid dissatisfaction.

A summary of each of the motivation indicators described by Herzberg (Ruthankoon 2003, apud Haruna 2013, p.5), is as follows:

- *Achievement*. An example of positive achievement might be of an employee who completes a task or project before the deadline and receives high reviews, increasing his satisfaction. However, if that same individual is unable to finish the project in time or feels rushed and is unable to do the job well, the satisfaction level may decrease.
- *Recognition*. When the employee receives the acknowledgement, he deserves a complimentary for a well-done job, and the satisfaction will increase. If the employee's work is overlooked or criticized, it will have the opposite effect.
- *Work Itself.* This involves the employee's perception of whether the work is too difficult or challenging, too easy, boring or interesting.
- *Responsibility.* Is the degree of freedom an employee has to take his/her own decision and implement his/her ideas. The more liberty he has on that responsibility, the more inclined the employee is to work harder on a project and increase his satisfaction with the result.
- *Advancement.* This refers to the expected or unexpected possibility of promotion. An example of negative advancement would be if an employee did not receive an expected promotion.
- *Possibility of Growth.* This includes the chance one might have for advancement within the company. This could also include the opportunity to learn a new skill. This could have a negative effect on the satisfaction the employee feels with his job and position.

The following are the hygienic indicators, which work in the same way with positive or negative attributes. However, these factors can only have an effect on dissatisfaction.

- *Company Policy or Administration.* The employee's perception of whether the policies in place are good, bad, fair or not, may change the level of dissatisfaction.
- *Personal or Working Relationships.* This indicator refers to relationship of the employee with his supervisors, his peers, as well as his subordinates. The way someone feels about interactions and discussions that take place within the work environment can also affect satisfaction.
- *Salary.* This factor is straightforward. Increase or decrease in wages has a great impact on satisfaction or dissatisfaction.
- *Personal Life.* Although people try to separate work from personal life, it is inevitable that one will affect the other.
- *Feeling of Job Security.* This is a significant factor. The sense of job security in the company, as well as a position within the organization is very important regarding the level of satisfaction.

According to Lundberg et al. (2009), to achieve employee's motivation, managers must give responsibilities to their employees and create platforms for feedback.

3.2 Data Sources for Indicator Quantification

The three main sources for obtaining data for the quantification of indicators are: (i) 360º evaluation; (ii) data sources of the human resources department; and (iii) data collected from social networks and communication channels.

3.2.1 360-degree Evaluation

Modern evaluation systems include a more balanced and holistic approach, conveying the performance of everyone in the organization. This proposal provides a flexible 360-degree evaluation framework where executives, managers and employees (with peer review) can express their judgments in different domains. The results can be expressed linguistically, numerically or in intervals. Figure 1 (adapted from Espinilla et al. 2013) presents the proposed 360-degree assessment.

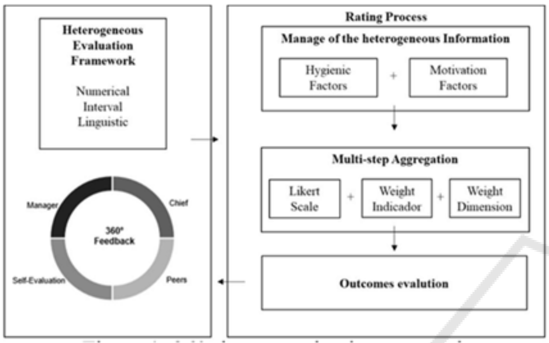

Figure 1: 360-degree evaluation proposal.

Sources of information work with hygienic and motivational factors, which together lead to the aggregation of results. That is, the result of the evaluation process occurs after the aggregation of the indicators on a Likert scale, given the importance attributed to the indicator and to the dimension. Therefore, the evaluation considers the interaction between the evaluated criteria, its relevance and the importance of all of those involved in the process.

3.2.2 Human Resources ERPs

The main data to be obtained from the Human Resources are the hygienic and motivational indicators, which include the following: (i) Position; (ii) Salary; (iii) Health / Insurance Plan; (iv) faults and delays; (v) medical absence.

Such data can normally be obtained in ERP systems. For the purpose of motivational analysis, the ideal is to organize this data in specific files, so that they can generate information about the hygienic and motivational factors. Historical data from employees' such as positions held over time, salary changes, awards, faults and delays can be stored and updated regularly, thus becoming a valuable source for motivational analysis.

Figure 2 presents some complementary data, such as information about salary paid in the market, based on the Brazilian Occupation Code. In addition to this data, other information can be obtained from the controls of HR and external sources. As above mentioned, ideally, this information should be organized in a DataMart, where the load with updating of the data is regularly done. The HR Department can provide information about the employee profile, salary history and attendance, opportunities for promotion, policies and benefits, among others.

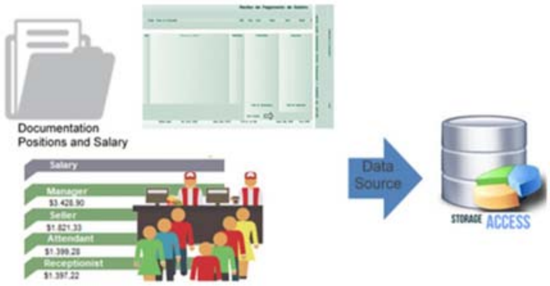

Figure 2: Data sources from HR Department.

Existing methods range from machine learning methods, exploiting patterns in vector representations of text for lexicon-based methods. This is done taking into account the semantic orientation of individual words. These words are matched with a sentiment lexicon, extracting their associated sentiment.

With this information it is possible to check the history of positions held, salary increases, received awards, attributed responsibilities during the career, salary positioning in relation to job market, among other indicators.

3.2.3 Analysis of Sentiments

In order to use analysis of sentiments, it is important to identify the domain related to the text. For example, to perform analysis of sentiments related to indicators such as Company Policy and Management, Relationship with the Chief, Work Conditions, and so on, it is first necessary to identify the domain relates to such indicators. This can be done using Latent Semantic Analysis (LSA) techniques. In this way it is possible to identify the domain and to carry out analysis of sentiments, selecting the word sense with the highest semantic similarity to the context.

The techniques are applied in two phases: pre-processing and processing. In the first one, the algorithm changes text words to lowercase and performs removal of accents. In the second one, stopwords removal techniques and lemmatization is applied.

Figure 3 (adapted from Hogenboom et al., 2013) shows a schematic view of the analysis of sentiments from input documents, and returns results based on word scoring. The presented method first splits a document into paragraphs, sentences, and words using n-grams techniques. Then, for each sentence, the Part-of-Speech (POS) and lemma of each word is determined. In lemmatization, text words are reduced to their radical, eliminating effects of verbal times in sentiment interpretation, as well as gender and number variations.

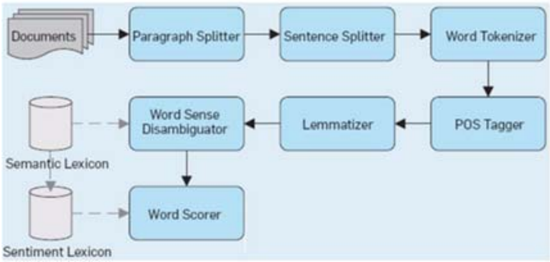

Figure 3: Schematic view of sentiments analysis.

The word sense is subsequently disambiguated using an unsupervised algorithm. It iteratively selects the word sense with the highest semantic similarity to the word's context. The sentiment of each word, associated with its particular combination of POS, lemma, and word sense, is then retrieved from a sentiment lexicon like SentiWordNet.

Figure 4 presents analysis of sentiments, showing part of data collection, classification, summary and results.

Figure 4: Collect and process data for the analysis of feelings.

This data can be collected from social networks such as Twitter, LinkedIn, Facebook, Instagram (as long as the data is public). Social networking sites are considered a good source of information because people freely share and discuss their opinions on a given topic. Such information can be positive, negative or neutral, as well as portraying happiness, well-being, sadness, bipolarity, among other motivational characteristics.

In order to obtain a good analysis, it is necessary to use the sentence level or keywords, with the purpose of classifying the domain of sentiment expressed in each sentence.

4 EVALUATION MODEL

The objective of the proposed approach is to provide information about the work as a whole in order to obtain a balanced and holistic view of motivational evaluation. For dynamic motivational analysis, we create a framework composed by three dimensions:

i. *360-degree Evaluation.* The enquiry will be conducted through the use of questionnaires. The objective of this process is to obtain an evaluation of each employee in relation to the organization as a whole.
ii. *Human Resources.* The results of the model will indicate different dimensions of employees' motivation with a direct influence on increasing human resources performance.
iii. *Sentiment Analysis.* Data collected from social networks and communication channels for analysis of sentiments. Here, we want to analyze sentiments related to indicators such as company policy, relationship with the chief, work conditions, and so on.

4.1 Indicators Evaluation

The evaluation of the indicators considers the Likert scale of five points: (5) excellent, (4) good, (3) neutral, (2) poor and, (1) bad. Thus, response to higher levels corresponds to greater satisfaction with the organization or the indicator, or even one area compared to another. For each indicator, a weighting factor can be used when assigning a given quantitative value.

Some methods of weighting are derived from statistical models such as factor analysis, data development analysis and unobserved component models (UCM). Budget allocation processes (BAP), analytic hierarchy processes (AHP), and conjoint analysis (CA) (OECD, 2008) are other methods. Regardless of the method used, weight is an essentially valuable judgment.

This research proposes the use of the linear aggregation method, in which the value attributed to the indicator by the Likert scale is multiplied by the respective weight, thus obtaining the relative importance of the indicator within the analysis set.

In addition to analysing indicators individually, organizations can use statistical models such as Principal Component Analysis (PCA) or Factor Analysis. In this way, it is possible to group individual indicators according to their degree of correlation, and then proceed with correlation analysis of indicators.

Table 1 shows the three-dimensional framework. Data were considered to be fictitious of the evaluation result for an employee. The approach uses a set of indicators that are punctuated in a three-dimensional framework, considering a dynamic system of assigning vertical and horizontal weights. The table identifies the two main categories of indicators, according to Herzberg's Two Factor Theory.

Table lines show the indicators, which are scored in each of the three dimensions according to the Likert scale. The indicators that correspond to the hygienic factors in Herzberg's theory are located in the top of the table, while the motivational indicators are at the bottom in darker tones.

Table 1: Three-dimensional matrix for dynamic evaluation.

INDICATORS	weight	0,2					0,3					0,5					Results
		I - 360° Evaluation					II - Human Resources					III - Sentiment Analysis					
		Dimension weight = 20					Dimension weight = 30					Dimension weight = 50					
		5	4	3	2	1	5	4	3	2	1	5	4	3	2	1	
Company policy and management	1		4											5			5,0
Supervision	1			3								5					4,4
Relationship with the leader	1	5														1	2,1
Work conditions	1		4									5					4,7
Salary	1		4					4						3			3,5
Relationship with colleagues	1	5												3			3,6
Relationship with subordinates	1	5												3			3,6
Personal life	1		4													1	1,9
Safety	1		4					4						3			3,5
Assiduity	1		4								1		4				3,1
Achievement	1			3			5							3			3,6
Recognition	1				2			4						3			3,1
Work itself	1		4													1	1,9
Responsability	1			3			5								2		3,1
Carreer advancement	1		4					4						3			3,5
Professional growth	1		4				5							3			3,8

In the example, weights can be assigned to the indicators (column 3). Therefore, the calculation to find the degree of motivation will depend on the situation of the employee in relation to each indicator plus its development in every dimension. In addition, some indicators do not have data (supervision, Relationship with the leader, colleagues and subordinators, work itself, and so on), because these data is not obtainable in the Human Resource dimension. The last column shows the resultant score after the calculation and weighting of the horizontal and vertical weights.

The company can choose a weight of 1, 2 or 3 for each indicator (in the example, a default value of 1 is shown). The same can be used for the dimension’s evaluation. For example, in the Dimension 360 degree a weight of 20 was assigned. The dimensions Human Resources and Analysis of Sentiments received weight 30 and 50, respectively.

The weights can be changed (that is, they are variable) according the company`s external or internal factors. External factors refer to the supply and demand of labor, the economic context (inflation, exchange rate, employment level, exports) and so on.

4.2 Clusters Identification

The results obtained in the evaluation of the indicators will be used to identify clusters. Among similarity metrics, Euclidean distance is one of the most commonly used (Carvalho et al. 2006). According to Moita Neto and Moita (1997), in cluster analysis the similarity between two samples can be expressed as a function of the distance between the two points represented in n-dimensional space. The most usual way of calculating the distance between two points a and b in the n-dimensional space is known as the Euclidean distance.

According to Kaufman and Rosseeuw (2009), Euclidean distance is the most common metric and can be combined with weights in the variables, depending on the importance of each attribute in the description of an object. The formula is as follows:

$$d(a,b)=\sqrt{w_1\cdot(a_x-b_x)^2+w_2\cdot(a_y-b_y)^2+w_3\cdot(a_z-b_z)^2+[\ldots]+w_n\cdot(a_n-b_n)^2} \quad (1)$$

Where:

- *d (a, b)* = similarity metric between object "*a*" and object "*b*", where the closest to 0, the more similar the objects;
- *w* = weight of each attribute;
- *ax* = attribute value *x*, from object *a*, on the *x*-axis;
- *bx* = attribute value *x*, of object *b*, on the *x*-axis

In the problem proposed for this work, an employee is a point on the n-dimensional Cartesian plane, he/she is represented by: a = {x, y, z, ..., n}, that is, each plane (x, y, z, ..., n) represents an attribute of the Herzberg factor (ex. Realization, Recognition). The distance will always be calculated between two employees, so that the closest to 0 score, the more similar is the motivation degree among then.

5 RESULTS OVERWIEW

The graphical user interface applied to present the results is based on the calculation and presentation of clusters for an overview. It is possible to visualize the motivational score of a employee, a department, or a section, using drill-down techniques.

In the context of this work, clusters are formed by employees who obtained similar indices, as shown in Figure 5. The vertical axis represents the number of employees, while the horizontal axis represents the degree of motivation resulting from the matrix. The points in the graphic represent the scores presented in the Results column in Table 1.

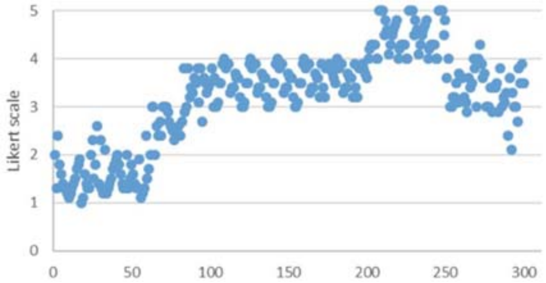

Figure 5: Presentation of results in clusters.

Each point presented in Figure 5 refers to the degree of motivation of each employee. As can be seen, about 25% of the employees are poorly motivated (ranging from 1 to 2.9 on the Likert scale); 60% are motivated (ranging from 3 to 4 on the Likert scale), and 15% are highly motivated (ranging from 4.1 to 5 on the Likert scale).

Figure 6 shows details of the drill-down technique. The idea is that by clicking on a cluster or point, a detailed representation of that point can be visualized. In the same way, each representation can offer the vision of the indicators of an employee.

Figure 6: Detailing an employee motivation indicator.

Important accentuate that results obtained individually by employees can be consolidated by section, department, area, rising in the hierarchy using drill-up technique. Likewise, the indicators can be viewed at the highest levels of the functional hierarchy and go down the hierarchy to examine the lower levels using the drill-down technique.

6 DISCUSSION AND CONCLUSION

For decades, job motivation has been shaped under static approaches, neglecting the dynamics of the job market and the ability of employees to obtain information. As a consequence, the collected evaluations did not allow to gather the richness of the information coming from several sources. Our approach considers that there is a improvement of motivational analysis when the evaluation system works with a wide range of assessments from several sources.

During observation phase and data gathering work, it was verified that, in practice, the motivation assessment was mostly based on questionnaires, which occurred in long frequency periods, averaging 6 to 12 months. For the most part, they do not reflect the current situation because in long times periods many indicators can change. In fact, the majority of indicators are constantly changing, either by internal or external influences.

The great advantage of working with a dynamic approach is the possibility of predicting situations that may affect the motivation of an employee or a group, and then take preventive measures. The analysis of sentiments can disclose new characteristics of the evaluation process, at any moment. In this way, employees can be evaluated using several domains of expression.

The presented approach allows evaluation of the degree of employees' motivation. It was developed in conjunction with the HR team of a large company, including researchers in the areas of Enterprise Administration and Computing. Therefore, the main contribution of this paper is the development of a framework for dynamic assessment of employee's motivation, as opposed to current static approaches. We could not find an approach with such characteristics in literature, which makes the approach innovative.

REFERENCES

Akdemir, E., Arslan, A., 2013. Development of motivation scale for teachers. Procedia-Social and Behavioral Sciences, 106, 860-864.

Alharthi, R., Guthier, B., Guertin, C., El Saddik, A., 2017. A dataset for psychological human needs detection from social networks. IEEE Access, 5, 9109-9117.

Carvalho, D. F., Santana A.C., Mendes F.A.T. 2006. Análise de cluster da indústria de móveis de madeira do

Pará. Novos Cadernos NAEA, Belém, v. 9, n. 2, p.25-53, dez. 2006. ISSN 1516-6481.
Chumkamon, S., Masato, K., Hayashi, E., 2015. Facial Expression of Social Interaction Based on Emotional Motivation of Animal Robot. In Systems, Man, and Cybernetics (SMC), IEEE International.
Espinilla, M., de Andrés, R., Martínez, F. J., Martínez, L., 2013. A 360-degree performance appraisal model dealing with heterogeneous information and dependent criteria. Information Sciences, 222, 459-471
Haruna, M., 2013. An Empirical Analysis of Herzbergs Two-Factor Theory. Nigerian Journal of Management Technology & Development.
Herzberg, F., 1971. Work and the nature of man. New York: World Publishing.
Hogenboom, A., Bal, D., Frasincar, F., Bal, M., de Jong, F., Kaymak, U., 2013. Exploiting emoticons in sentiment analysis. In Proceedings of the 28th annual ACM symposium on applied computing (pp. 703-710). ACM.
Kaufman, L., Rousseeuw, P. J., 2009. Finding groups in data: an introduction to cluster analysis (Vol. 344). John Wiley & Sons.
Kelley, D. J., Waser, M. R., 2018. Human-like Emotional Responses in a Simplified Independent Core Observer Model System. Procedia Computer Science, 123, 221–227.
Lundberg, C., Gudmundson, A., Andersson, T. D., 2009. Herzberg's Two-Factor Theory of work motivation tested empirically on seasonal workers in hospitality and tourism. Tourism management, 30(6), 890-899.
Matei, M. C., Abrudan, M. M., 2016. Adapting Herzberg's Two Factor Theory to the Cultural Context of Romania. Procedia-Social and Behavioral Sciences, 221, 95-104.
Maslow, A. H., 1963. A theory of human motivation. Psychological review, 50(4), 370.
Medhat, W., Hassan, A., Korashy, H., 2014. Sentiment analysis algorithms and applications: A survey. Ain Shams Engineering Journal, 5(4), 1093-1113.
Moita Neto, J. M., Moita, G. C., 1998. Uma introdução à análise exploratória de dados multivariados. Química Nova, 21(4), 467-469. https://dx.doi.org/10.1590/S0100-40421998000400016
Ravi, K., Ravi, V., 2015. A survey on opinion mining and sentiment analysis: tasks, approaches and applications. Knowledge-Based Systems, 89, 14-46.
Shen, C.-Y., Yu, K.-T., 2009. Enhancing the efficacy of supplier selection decision-making on the initial stage of new product development: A hybrid fuzzy approach considering the strategic and operational factors simultaneously. Expert Systems with Applications, v. 36, n. 8, p. 11271-11281.
Tay, L., Diener, E., 2011. Needs and subjective well-being around the world. Journal of personality and social psychology, 101(2), 354.
Toy, B. L., 2014. Applying behavior models in a system architecture (Applying an engineering protocol structure to AI). In Computational Intelligence for Human-like Intelligence (CIHLI), IEEE.Ciência da Computação) – Universidade Estadual do Ceará. Centro de Ciência e Tecnologia.