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Research Paper

Clustering tool usage to align a company strategy to its talent management needs

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Structured Abstract

Purpose: This paper describes a *k*-means clustering study carried out with a group of employees from a Brazilian company. The assessed variables refer to individual and demographic characteristics of subjects in this population.

Design/methodology/approach: The idea is to gather data that represents individual and demographic characteristics and to generate groups of individuals through cluster analysis. Common characteristics of individuals inserted in these groups are then evaluated to identify behaviour patterns and generate improvement initiatives regarding human development.

Findings: The results suggested the formation of two groups or workforce members regarding their differences in wages, age, company experience and number of overtime work hours. For each obtained group, a set of managerial strategies were described.

Originality/value: The search for appropriate tools to address people management has become an issue of interest in companies of different segments. Such tools aim to better understand employees' behaviour tailored to improve the allocation of investments in the workforce. In that scheme, workforce members presenting different characteristics can receive proper corporate strategies.

Keywords: Clustering, *k*-means, Talent management.

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1. Introduction

Companies have devoted increasing efforts to guide their actions for the well-being of their employees. In this sense, the quality of life at work has been researched since the 70's and in many fields. Rossi, Lipsey & Freeman (2003) point out that decision-makers must find ways to allocate scarce resources to optimize their use, aiming at addressing the issues of technical qualification and behavioral aspects (referring mainly to attitudes in the workplace).

Among the studies of the past decade, the concept of people analytics (also known as talent analytics and human resources analytics), initially used in large technology companies, was raised in order to transform the data and metrics of Human Resources (HR) in rigorous knowledge (Boudreau & Ramstad, 2004; Al Ariss, Cascio & Paauwe, 2014). This knowledge should be conducted so that the businesses take clear and assertive decisions on important information about human potential. Therefore, a logical structure should ensure that the analysis is focused on certain issues for data discovery and results that are actionable (Levenson, 2011).

Davenport, Harris & Shapiro (2010) suggest the existence of six branches in people analytics: (*i*) the so-called facts of human capital, working the main indicators of individual performance and enterprise level; (*ii*) analysis of Human Resources, which seeks to gather data of different natures to gain insights into specific departments or functions; (*iii*) Investment Analysis on Human Capital in order to identify actions that substantially impact on business performance; (*iv*) Estimated Workforce, which analyzes turnover, succession plans and other data order to identify excess or shortage of manpower in advance; (*v*) Value Model for Talents, which maps the definition of value for employees and thus create models to increase retention rates; and (*vi*) the Talent Supply Chain, which helps companies to make decisions regarding several workforce aspects; e.g. optimization of working hours and adjustment of demand forecast sales in a commercial area.

Among the groups suggested by Davenport, Harris & Shapiro (2010), Analysis of Human Resources and Investment Analysis on Human Capital are complementary studies as the former generates databases and hypotheses for the application of the latter. Further, no well succeeded organization has used only one of the methods.
Boudreau & Ramstad (2004) emphasize that a hard task lies in creating an organizational structure and a people management system that involves skills beyond those typically assessed by HR models. Therefore, it is necessary to seek information beyond personnel management areas in order to understand logic behind each organization and to propose solutions to talent management.

Thus, the main purpose of this study is to identify groups of workforce members presenting common features in order to propose strategies aligned with the needs of each group, providing conditions for improving performance and quality of life at work. The idea is to gather data that represents individual and demographic characteristics (DuBrin, 2003) and to generate groups of individuals through cluster analysis (Hair et al., 2009). Common characteristics of individuals inserted in these groups are then evaluated to identify behavior patterns and generate improvement initiatives regarding human development.

The propositions depicted in this paper are of relevance as companies have increasingly tried to retain good employees by providing them welfare benefits and investments in education. The identification of clusters among employees through a statistical technique can generate the necessary basis for the adjustment of development plans, aligning expectations between company and employee.

This paper is organized as follows: after the contextualization of the topic and definition of the article's goal in the Introduction, follows the section 2 which presents the literature review on the people management issues and clustering techniques. The methodological procedures are presented in Section 3, followed by the description of the results in section 4. Section 5 presents the conclusion of the article with a discussion of the results.

2. Theoretical framework

This section presents a literature review on the topics covered in the survey, which are divided into three subsections: the first presents aspects of organizational behavior, the second comments on the importance of the characteristics evaluated in each individual and the third presents fundamentals of clustering tools.

2.1. *Organizational behavior*

The concept of organizational behavior, which has been studied since the 1940s, is presented by Wagner III & Hollenbeck (2014) as a field of study that seeks to understand, explain, predict and change human behavior in organizational context. This line of science is divided into three dimensions: micro, meso and macro-organizational behavior (Lai & Lee, 2007; Wagner III & Hollenbeck, 2014). The micro scale studies the individual behavior of workers, while the meso dimension is focused on understanding the relationship between people working in teams and groups; the study of organizational macro behavior studies the behavior of organizations as a whole. Robbins et al. (2003) adds a fourth dimension: the external environment interacting with the organization.

This research is focused on the organizational micro behavior’s dimension as it works with individual variables describing employees’ behavior. It aims to identify similar characteristics in formed groups, generating basis for the creation of conditions to have a better overall business performance. Cascio & Boudreau (2010) emphasize that the analysis in Human Resources are important as they make vital decisions about the best talents and how they are organized. In this sense, Chi & Gursoy (2009) show that customers tend to have a better experience with companies that have employees with high levels of satisfaction and engagement, while Koys (2001) reports that the behavior as citizens by employees influences the profitability of organizations. In addition to these features, other relevant aspects related to organizational behavior are presented in the next section.

2.2. *Employees’ characteristics*

DuBrin (2003) argues that understanding differences among employees can lead to significant improvements in individual and organizational productivity. Thus, the author presents the main sources of individual and demographic differences among employees. Individual differences concern the way people react to the same situation based on personal characteristics; as for the demographic differences, they work with diversity in historical factors related to workforce that influence workers' attitudes and behaviors (Bloodgood, 2012).

According to DuBrin (2003), the main individual differences are: ability and talent; achievement of high-quality results; how people want to be empowered and involved; leadership style; need for contact with others; commitment and loyalty to the company; and self-esteem. In terms of demographic differences, it features (*i*) gender, (*ii*) age and experience, (*iii*) ethnicity and (*iv*) disability status (Minbaeva & Collings, 2013).

Thus, the concepts of the raised differences can be used to analyze groups to be formed. Campos (1992) states that productivity increase as "producing more and better outputs in a process with fewer inputs". Hunter, Schmit & Judiesch (1990) claim that the higher the level of complexity of a task performed by workers, the greater the variability in relation to the productivity of the task. In addition, Robbins et al. (2003) state that ability directly influences the level of performance and satisfaction of an employee.

As for differences on the propensity that each work has to achieve high quality results, DuBrin (2003) emphasizes that some people naturally tend to strongly pursue high quality because they are conscientious, have a good ability to be accurate and pride in their work. Similarly, less conscientious workers tend to have greater difficulties to achieve results equivalent to the first (Stahl et al., 2012; Faisal & Al-Esmael, 2014).
With regards to how people want to be empowered and involved, Horochovski & Meirelles (2007) mention that empowerment is a similar autonomy concept as it deals with the ability of individuals to decide on the issues that concern them and choose between alternative courses of action. In the view of DuBrin (2003), it is necessary to encourage employees to suggest improvements and give more autonomy to make decisions.

DuBrin (2003) & Vaiman, Scullion & Collings (2012) also note that people differ in leadership style. Many individuals seek the greatest possible freedom within a job and know how to deal with it, while others prefer to have their managers always around. People also need supervision at different levels: generally less skilled workers, less experienced and less motivated need a more constant supervision than other employees. On the need for contact with others, Soto (2002) defines the concept of sociability as the desire to share activities and get the other's attention and stimulation that is part of social interaction. Being sociable suppose intrinsically value the process of interacting with others.

On demographic differences are cited gender, age, experience, ethnicity and disability status. Regarding gender differences, experiments conducted by Powell (2011) concludes that women tend to have a more interpersonal style than men when dealing with co-workers. They also tend to be more democratic and, when in a leadership position, tend to be less autocratic. Still, the study shows that the way to accomplish the same task does not differ from men to women (Birasnav & Rangnekar, 2010; Thunnissen, Boselie & Fruytier, 2013).

Mahlberg et al. (2013) tests hypotheses about the relationship of aging and productivity. The study showed no evidence that aging necessarily lead to a decline in labor productivity. DuBrin (2003) points out that evaluating age and experience has become relevant, considering that the inclusion of people in the economically active population in most western countries does not correspond to retirement of older.

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When it comes to ethnic groups, the concept of race ethnicity is discussed (Cappelli & Keller, 2014). DuBrin (2003) says that, on terms of work performance and people behavior, these differences are more intensively attributed to culture than to ethnic or racial experience.
About differences on disabilities, the World Health Organization (1980) conceptualizes disability as loss or abnormality of structure or psychological function, physiological or anatomical temporary or permanent. It is important to pay attention to this aspect, since the disability, including mental, is gaining attention as a source of diversity in the workplace (Farndale et al., 2014). With the individual and demographic differences between employees presented, one can use variables that represent them to perform cluster analysis. In the next section, we present concepts about multivariate cluster formation.

2.3. *Tools for cluster formation*

According to Hair (2010), cluster analysis is a group of multivariate techniques intending to group objects based on their characteristics. The essential criterion is to maximize the differences between opposing groups (Dias Filho, Paulo & Corrar, 2007).

Cluster analysis methods are divided into two types: hierarchical and non-hierarchical. Hair et al. (2009) state that the hierarchical procedures comprise grouping techniques supported by phases, and involve a combination or division of objects into groups. The non-hierarchical procedures assign objects to a group once specified the number of groups to be formed (Dias Filho, Paulo & Corrar, 2007).

The non-hierarchical methods take advantage of the hierarchical when working with large data sets, as they do not require the calculation of similarity matrix for all observations, only the calculation of the similarity between each observation and the centroid of the cluster. In addition, non-hierarchical methods are less sensitive to outliers, distance measurement, and inclusion of irrelevant variables (Hair, 2010).

The non-hierarchical algorithms generate a number specified by the user and then allocate observations to clusters until some numerical criterion is fulfilled (Hair, 2010). Each of these observations contains values for each variable used in the characterization of the sample to be clustered. To run the algorithm, distance measurements as the Euclidean distance (distance from a straight line drawn between two points) are used between observations and between the groups.

To assess the quality of the groups formed by the clustering tools, Rousseeuw (1987) introduced the concept of silhouettes to interpret and validate the results of cluster analysis. Thus, the Silhouette Index (SI), presented in equation (1), evaluates how an object is similar to other objects in its group compared to the objects allocated in the closest group (Stroieke, Fogliatto & Anzanello, 2013). The higher the index value, the better the allocation of the object to its final cluster. $SI(i)$ ranges from -1 to +1, and SI values near +1 denote proper allocation of observations to clusters.

$$SI(i) = \frac{b(i)-a(i)}{\max\{b(i),a(i)\}}, \qquad (1)$$

where $a(i)$: is the average distance of i observation in relation to other observations by the group that has been allocated; and $b(i)$: is the average distance of i observation in relation to the observations of the nearest neighboring group.

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The *k*-means clustering technique has been used in the recognition of patterns of human behavior. Pimentel, França & Omar (2003) used the technique to identify groups of learners, while Horst, Martins Jr & Souza (2012) used *k*-means to evaluate employee's satisfaction in a hospital. Stroieke, Fogliatto & Anzanello (2013) used the algorithm to generate homogeneous groups of workers in learning curves; the results were measured through the Silhouette Index.

3. Methodological procedures

The suggested approach relies on five operational steps: (*i*) data collection; (*ii*) processing of data; (*iii*) generation and evaluation of grouping quality; (*iv*) interpretation of the formed clusters; and (*v*) proposal of managerial strategies for each group formed.

The first step consists of choosing and collecting data representing the individual and demographic differences proposed by DuBrin (2003). Such information was collected from the database system used by the Human Resources of the company (Wagner III & Hollenbeck, 2014), and was comprised of workforce data detailing hierarchic levels and performance evaluation. The databases were organized into arrays, where each column was a variable and each row represented a workforce member.

The second step preprocesses the data using two different approaches: data standardization and normalization. Both aimed to minimize problems due to different magnitudes of the clustering variables. In the standardization of data, the maximum and minimum values of all the variables are chosen: score 1 is attributed to the maximum value are score 0 to the minimum value; intermediate values are given proportional scores. In the normalization, average and standard deviation were calculated and the z score is calculated.

The third stage performs two procedures: it first generates the clusters and then evaluates the quality of the formed groups. The *k*-means clustering tool (Hair, 2010) was carried out using the *R* software (cluster package) for various values of k ($2 \leq k \leq 11$), which represent the number of groups to be formed. For each k, the quality of the clustering procedure was assessed using the average Silhouette Index (SI) (Rousseeuw, 1987); the group yielding the highest SI was chosen. A naïve variable selection procedure was also carried out by momentarily removing one variable from the dataset and performing the clustering using the remaining variables. The omitted variable leading to the highest SI was removed from the dataset given that the clustering quality was increased when that variable was left out of the procedure.
The fourth step is the interpretation of generated groups. For that matter, the internal prevalent characteristics of each group were identified, and experts assessed the factors explaining similarities and differences between groups.

In the last step, a set of managerial strategies were developed for each group identified in step four. These strategies were tailored to identify improvements regarding workforce members' well-being at work, training and compensation plan, among others. The number of shares was valued at prioritization by two aspects: the need for talent retention (employees with high performance and high growth potential) and feasibility of action.

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4. Results

The proposed method was applied to a conglomerate of Brazilian companies that are characterized as large-sized according to BNDES–*National Bank of Economic Development* (2013) criterion, located in four states of the Southeast and South regions. The company works in several sectors, with emphasis in communications and information technology, and presents a structure comprised of more than 5,000 employees. The method was applied to the Human Resources sector, which centralizes the processes related to workforce.

The database assessed was comprised of 2,152 observations (employees) described by seven variables representing the individual and demographic characteristics proposed by DuBrin (2003). Such variables are depicted in Table 1.

Table 1. Overview of variables to be used in the cluster analysis

Variable (code)	Meaning	Individual and demographic differences related	Measurement Unit
Satisfaction	Represents the overall satisfaction of the employee in relation to the company.	Individual differences of the need to contact the others, commitment, loyalty to the company and self-esteem.	-
Extra Hours	It represents the number of extra hours performed in the month used for the analysis (proportional to the minutes made).	Individual differences in productivity, ability and talent.	Hours
Age	Represents the age of the employee, proportional to the number of days at the end of the month used for the analysis.	Demographic differences in age and experience	years
Performance Evaluation Note (mhct)	Is the note given to the employee by his manager and a committee of Human Resources on the evaluation of the employee's performance in the previous quarter to the one used for the analysis.	Individual productivity differences and propensity to achieve high quality results	-
Total Remuneration (salario)	It is the sum of fixed and variable remuneration of the employee in the month used for the analysis.	Individual differences in productivity, commitment and loyalty to the company, skill and talent, demographic differences in age and experience	reais
Compa-ratio (comp_out)	It is the comparison of the employee's salary to the median of the market, i.e. comparison of the person's salary to the value practiced by other companies for the same work performed.	Individual differences in ability and talent and demographic experience differences	percentage

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Company Time (tempo_empr)	Represents the period of time started in the employee's hire date in the company and ended in the dismissal date (for employees dismissed on the date of analysis) or on the last day of the month used for the analysis (for employees hired on the date of analysis) proportional to number of days in the period.	Demographic differences experience and individual differences of commitment and loyalty to the company	years

Source: Adapted from Dubrin (2003).

The correlation between the variables was evaluated in order to identify redundant variables, as in Table 2. That table suggests that there is no high correlation between the variables, denoting that the database is comprised of variables addressing different aspects describing workforce members. The largest correlation is verified in variables "Company Time" and "Age"; it was decided, however, to keep both variables for treating different characteristics in micro-organizational behavior (specifically, individual and demographic characteristics).

As mentioned in section 3, the database was preprocessed in two ways before running the clustering algorithm: standardization and normalization. SI results showed that standardized data outperformed the normalized, both in the case where all variables were used, as in cases where removal of variables was performed. These attempts were carried out in stages: first, with the seven variables in the model, tests were carried out with the omission of all variables one by one. The model that generated the largest SI was chosen and the procedure was repeated until only two variables were left in the model. Figure 1 illustrates SI profile for the standard data as the number of variables was decreased. Considering the increase in SI and the context of variables in the company, we decided to remove the variable "Satisfaction" from the analysis. The remaining variables were retained: performance evaluation score, age, compa-ratio, company time, total remuneration and extra hours. Figure 2 shows SI values for each value of k in the arrangement in which these variables were retained. Based on such results, it is suggested the formation of two groups of workforce members (k = 0.3907). Figure 3 brings the formed groups.

Table 2. Correlation measures between the variables used in the database

Correlation	Performance Evaluation Score	Total remuneration	Compa-ratio	Age	Satisfaction	Company Time	Extra Hours
Performance Evaluation Score	1.0000						
Total remuneration	0.1763	1.0000					
Compa-ratio	0.0759	0.1805	1.0000				
Age	-0.0245	0.2156	0.4204	1.0000			
Satisfaction	0.0883	0.0806	0.0717	0.1341	1.0000		
Company Time	0.0165	0.1177	0.2658	0.6919	0.0638	1.0000	
Extra Hours	-0.0226	-0.0911	-0.1056	-0.0649	-0.0816	-0.1055	1.0000

Figure 1. Silhouette Index values for the number of variables retained in clustering

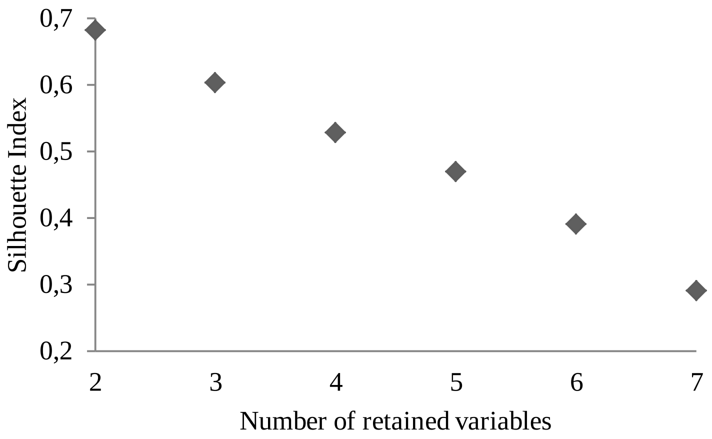

Figure 2: SI values for each number of groups formed in clustering without the variable Satisfaction

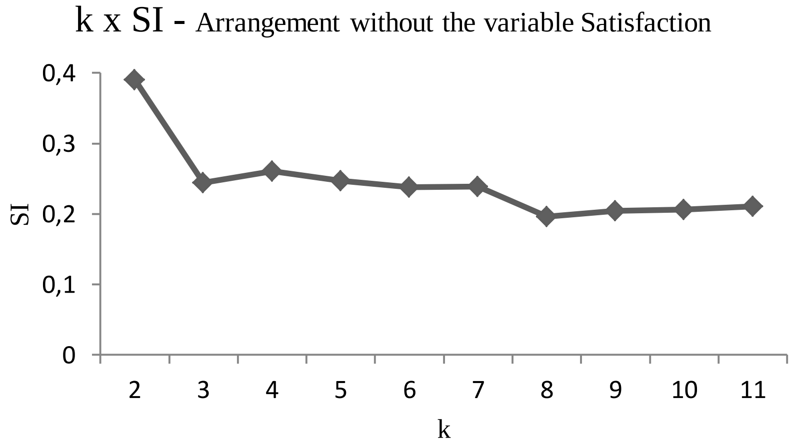

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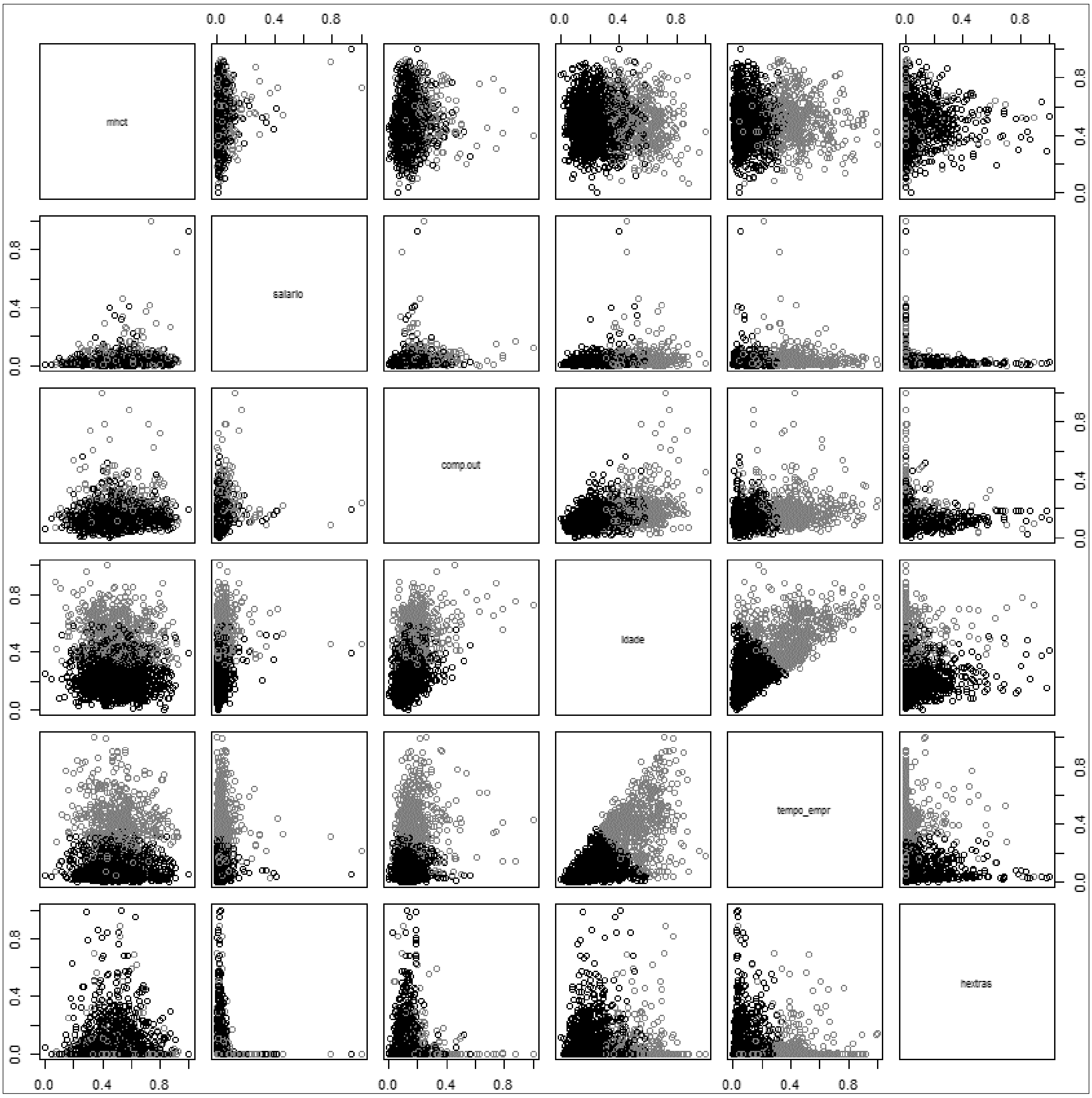
Figure 3. Dispersions of clusters generated by clustering



After expert analysis of the formed clustered, it was revealed that one of the groups (represented by the color black in Figure 3) was composed of employees with higher age, who perform less extra hours and present more company time. In addition, members from that group tend to have higher wages than the other group. Based on such exploratory results, the following managerial decisions were suggested:

(a) Promotion of a more attractive pension policy for these employees, so that these members could invest more in their careers while still working in the company;

(b) Creation of a remuneration policy of greater impact, giving more weight in the total compensation for the variable income and less for the fixed income. Thus, there would be more reason to promote this public engagement in financial matters of the company; and

(c) Conduction of a customized career monitoring for those members, aiming more security check about the paths that these people intend to follow at their careers.

On the other hand, the group presented in black in Figure 3 presented a younger profile: members performed more overtime hours, presented less company time and received lower wages than the black group. In relation to this group, the following measures were suggested:

(a) Possibility of a mentoring program for individuals in the group. Colleagues with more experience could provide valuable recommendations in that sense;

(b) Stronger investments in internships and trainee programs than currently performed; and

(c) Proposition of additional training programs on subjects of interest. That would compensate for the fact that they are receiving proportionally less money than the other group.

The implementation of actions aligned the company's strategy requires the definition of an action plan involving the human resources staff, managers, employees and external stakeholders. Thus, such definitions may be used as guidelines to future propositions.

5. Conclusions

This study sought to identify groups of workforce members presenting common characteristics based on clustering. Results were expected to assist in the development of strategies aligned with peoples' needs, increasing life quality at work and leading to better individual and team performances.

The proposed method relied on the non-hierarchical clustering by *k*-means and Silhouette Index as a quality index of the formed groups. Data describing members profile and features were initially preprocessed (standardized or normalized scale) in order to avoid distortion in the clustering process. Once groups were formed, the study proceeded to the interpretation of the cluster members and company's proposition of strategies for the obtained groups.

The proposed method was applied to a group of companies associated with communications and information technology. Variable withdrawal tests showed that the normalized data outperformed the standardized. During the tests for variable removal, it was noticed that "Satisfaction" did not significantly collaborated to identify groups of employees. This fact, associated with prior knowledge of the business context, resulted in the withdrawal of this variable from the database. The clustering resulted in two groups of employees. One of them consisted of individuals with increased age, company time and salary and less overtime performance in relation to the other group. For each group, a series of strategies aligned with the identified profile were generated.

The method here proposed can be extended to other datasets regarding workforce description comprised of a larger number of observations (members) and variables.

That would provide the method with chances to deeper assess the relevance of variables describing workforce behavior (as the dataset evaluated in this manuscript presented only seven variables). Major limitations of the framework here proposed rely on two fronts: (*i*) process experts need an undeniable ability to interpret the characteristics from each formed group, and to link that with the current situation of the company; and (*ii*) the development and implementation of well suited managerial plans for each group typically require knowledge on the financial situation of the company, since such plans depend on investments.

For future research opportunities, we suggest to use categorical variables representing micro-organizational characteristics. To this end, it is necessary to use a clustering tool or measure of distance that suits the use of continuous and categorical variables in the same arrangement.

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