Transforming HR and Improving Talent Profiling with Qualitative Analysis Digitalization on Candidates for Career and Team Development Efforts

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Transforming HR and Improving Talent Profiling with Qualitative Analysis Digitalization on Candidates for Career and Team Development Efforts

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Abstract. The digital transformation of HR is the new normal in the enterprise business world, in quantitative analysis side, but the decision making will remain qualitative for the long unforeseen future. We present digital qualitative methods for talent profiling in order to understand each team member's mindset, by utilizing brainstorming type questionnaire data. As a result of the study, a stand-alone solution is being developed which improves HR operations and talent profiling for individuals and organizations. Furthermore, this abductive approach indicates that this open-ended conceptual framework returns a promising qualitative analysis. The research work addresses the issues of the subjective nature of human resources with an open-ended approach which sharpens our decision-making without excluding it.

Keywords: HR · Human resources · Talent management · Profiling · Mindset · Digitalization · Digital transformation · Analysis · Brainstorming questionnaire

1 Introduction

Digitalization is the new normal in today's world. The world is changing fast, as technology is getting constantly smaller and sensors, plus computational capacity, in the edge of networks, is taking huge leaps forward. In a similar way, global digital transformation is pushing traditional business areas asset-based companies towards knowledge companies [33–35, 39]. Additionally, artificial intelligence solutions and sustainability-based practices [28–30, 59] are helping companies to transform their business operations through use of digital design process tools [12, 13]. Companies should be able to transform their HR practices to today's standards, by embracing the potions that digitalization can offer them as digital transformation of HR [1] is the new normal in the enterprise business world. But in the process, these new tools for HR should also help them e.g. find new employees with cultural fit personalities [32], support growth and innovation [33, 38], etc. Basically, the key is to not digitalize just for the fun of it, but instead, the goal should be efficiency with more precise and knowledge-revealing tools. In this context, this research provides answers to the issues which arise by qualitative analyses in human capital approach. By employing statistical techniques, rich visualizations, and brainstorming questionnaires, we aim to address the subjectivity which is inherent in qualitative approaches and decision making. In the world of recruitment and human resource management, nowadays, it is important to be able to combine traditional recruitment processes with modern team analysis [57] and be able to apply approaches where possible new employees under consideration could show their skills in practice, like in university – industry collaborative hackathon events [41, 61–64]. Furthermore, by employing mindset mapping tools, most suitable candidates get hired, enhancing RDI and development teams' productivity. The goal is to reveal a new, novel way which adds value in HR people analytics work [43] by employing common data science and survey tools, but with an innovative approach [6]. Initially, two basic research questions are set:

(1) Does this brainstorming type questionnaire, combined with demonstrated toolset, work effectively as a mindset mapping and visualization tool to help HR being more precise in their recruitment process?
(2) What values the comparison of respondents' mindsets could provide to HR operations?

The main hypothesis is that brainstorming type standardized questionnaires can be used as a map to unfold a candidate's mindset. The critic about standardized tests, questionnaires and surveys is quite harsh due to its closed structure, because they do not provide the option of a spontaneous answer [10]. However, they can be a powerful tool for research and development through an evolutionary approach [2].

Educators claim that standardized tests and questionnaires do not cultivate creativity, and to some extend that is true [10]. However, talent assessment can be approached by employing brainstorming questionnaires on a variety of topics, when respondents choose the most representative answer which they mostly agree with. Therefore, if the variety of topics is extensive, there is both broad and narrow focus, and the options are not biased which is an inherent characteristic of questionnaires, respondents will unfold their values, inclinations, and their mindset.

In a word, the most successful approach for talent profiling is an abductive approach with open-ended clusters as topics. The open-ended approach which sharpens our decision-making without excluding it [5, 8, 9] helps to address the issues of the subjective nature of human resources. Also, in this research case, the abductive approach offers opportunity to indicate the value of open-ended conceptual framework [3, 4, 7]. Generally, in social sciences, it can be said, that it is worth trying to be approximately right and not precisely wrong. Consequently, a map is being built with directions and orientations but not clear-cut borders. The key-point for respondents is to choose freely or not even choose at all.

2 Creating the Questionnaire Set

Technically, this questionnaire is created by using the Shinyforms Package of R open-source tools. However, the purpose of such a questionnaire is the respondent's profiling.

Therefore, its content aims to map the respondent's mindset. As basis for creating the questionnaire set, the following structural base components were used:

- Gardner's multiple intelligence theory [12]
- Management theory [13]
- Business practitioners to construct a questionnaire for talent profiling
- Big Five personality traits: OCEAN (Openness, Conscientiouness, Extraversion, Agreeableness, Neurotism) [11, 14].

OCEAN is used by HR practitioners to evaluate how candidates and marketers understand the potential customers of their products. Additionally, this questionnaire is focused on brainstorming, meaning that the research did aim to unfold the respondent's mindset but not to test them for their knowledge or their capacity. Moreover, this questionnaire contains statements and not necessarily questions, since the goal is to visualize the respondent's mindset creating his talent fingerprint. Hence, mind mapping was employed through brainstorming by searching mainly for semantics at the respondent's answers. By utilizing of the previously mentioned content sources, a brainstorming type questionnaire with seven sections (Temperament, Individuality, Interconnection, Culture, Communication, Character and Skills [11, 44, 45]) was created. In the following, these seven sections are presented one by one.

Temperament is a term which defines the personal traits of an individual, as well as their values and attitude. However, it is an economic term, too. It is important, both in business and in life, to know yourself - where you stand and where you want to end up. In practice, temperament, by and large, defines the expertise, the profession, and the field in which an individual pursues a career [14].

Individuality is closely connected with Character and Temperament, but it expresses the uniqueness of an individual which makes them different from the group. Therefore, individuality is what makes a person be an independent thinker and doer, even though they might have similar traits and behaviors to other people [15, 16, 21].

Interaction is relevant to Communication, but expression is not at its core. For that reason, the main aspect is how an individual or a team interacts with the world. Interaction is critical in innovation, research, product development, investing and any other activity where micro and macro are mutually related. In a word, perception matters in action and interaction [17].

'Culture eats strategy for breakfast', a famous quote, was credited to management consultant Peter Drucker [50]. Culture is not only the background, experience, and orientation - it is identity too. People behave according to their beliefs and thoughts as much as to their environment [22, 23]. However, some environments allow talents to flourish and others do not [18].

Communication is at the heart of team building. Bringing people together who speak different 'languages' is the way to succeed in terms of growth, productivity and innovation [10, 24]. Consequently, great achievements in business and science are not coming by mixing up the ingredients [27]. It is not a simple sum that generates great outcomes. Great products are the result of dynamic relationships.

In terms of **Character**, 'Hire Character, train Skill' is a widely known quote credited to former CEO of Porsche, Peter Schutz. Meaning that, quite often, character and cultural fit are more important than skills, although it is more difficult to get it right due to its subjective nature. The qualities of an individual belong to a long-term strategy which is what really matters if it is combined with competence, strong work ethic and willingness to learn. As it is said, skills can be taught or developed, though it is easier said than done. On the other hand, character cannot be changed as regards its core principles, values, and life view. As the author Zig Ziglar succinctly put it, "You don't build a business, you build people, and then people build the business".

Skills is a term which is used to describe technical knowledge of different forms and levels, but skills go far beyond that [19]. Day by day, skills become a behavioral aspect of our own personality. That is why talent is a reference not only for work, business, and social life but, also, for sharing ideas, beliefs, and values [49, 50]. Nevertheless, talent is as much common as scarce. It is said among techies and geeks that good engineers can be ten to hundred times better than mediocre ones. However, the question will be 'Is it teamwork or individuality which matters most in organizations?' [31, 46] Of course, the answer depends on the context, the nature of skills and the leadership.

In each of the aforementioned seven sections of the questionnaire, relevant statements or phrases are used with a few available options. The respondent can choose up to 25 options in total, for each of these sections contains roughly 50 options. Each respondent can use their available options as they wish. The answers are stored (commonly in.csv files) and analyzed per section and collectively. A research milestone materializes with the terms they choose consistently, in a manner which shows preference and familiarity. Subsequently, the sections show the keywords which describe the respondent best, are of high-frequency and, also, are relevant, forming a topic or a cluster.

3 Text Analysis

At first, a dataset of single words is created, which consists of the respondent's answers without numbers, punctuation, grammatical prepositions and a collection of stop-words which provide no value to data analysis of natural language data.

Code Section 1. Popular Libraries

```
Popular R libraries are employed to develop the Questionnaire as web application:
library(shiny), library(shinyforms), library(shinyjs), library(shinyWidgets)

Moreover, natural language processing is implemented using R libraries:
library(tm), library(SnowballC)

Additionally, R libraries are being used for visualization:
library(wordcloud), library(RColorBrewer)
```

The TM package of R-Project processes the data and remove all the words which can skew the final results. A sample of the code follows:

Code Section 2. Text Mining

```
docs <- VCorpus(VectorSource(subVector))             #Load vector as Corpus
docs <- tm_map(docs, content_transformer(tolower))                    #Lowercase
docs <- tm_map(docs, removeNumbers)                          #Remove numbers
docs <- tm_map(docs, removeWords, stopwords("english"))   #Remove      common
stop-words
docs <- tm_map(docs, removeWords,)                           #Remove more words
docs <- tm_map(docs, removePunctuation)                      #Remove Punctuation
docs <- tm_map(docs, stripWhitespace)                #Clean-out white spaces
dtm <- TermDocumentMatrix(docs)                      #The final Output
```

The final vector output contains all words which represent the candidate's mindset for each section of the questionnaire. Then R tools for wordclouds, pie charts and heatmaps are used to analyze and visualize each dataset. Wordcloud analysis is employed for the entire dataset without clustering and then a clustered wordcloud analyzes and calculates the natural language data per section.

Code Section 3. WordCloud Function

```
wordcloudFunc <- function(){                         #wordcloud function
        subVector <- character()                     #vector to store options
        subIndex <- 1
        filePath <- paste("responses", idnum, sep = "/")
        filePath <- paste(filePath, "csv", sep = ".")
        singleFile <- read.csv(filePath)
        #Lood .csv files for each section
subCols <- ncol(singleFile)
        for(col in 1:subCols){
        subVector[subIndex] <- singleFile[1, col]       #store data in a sub vector
        subIndex <- subIndex + 1                }

        #Prepare the data
        docs <- VCorpus(VectorSource(subVector))  #Load the vector as Corpus
        docs <- tm_map(docs, content_transformer(tolower)) #Correct lowercase
        docs <- tm_map(docs, removeNumbers)                 #Remove numbers
        docs <- tm_map(docs, removeWords, stopwords("english"))    #Remove
common stop-words
        docs <- tm_map(docs, removeWords, c("can",  … "often"))
        docs <- tm_map(docs, removePunctuation)
        #Remove Punctuation
        docs <- tm_map(docs, stripWhitespace)
        dtm <- TermDocumentMatrix(docs)
        m <- as.matrix(dtm)
v <- sort(rowSums(m),decreasing=TRUE)
d <- data.frame(word = names(v),freq=v)              #The last Output as data frame
set.seed(2398)                                       #Set the seed for visualization
return(d)            }
```

Table 1 presents an example of a clustered wordcloud output for R. Results show the frequency of each single word, i.e. how many times it is repeated, for each section of the questionnaire separately. With this dataset, the clustered wordcloud is generated, meaning that each section at the wordcloud is plotted separately. On the other hand, the ‘total wordcloud’ is plotted considering the frequency of each single word for all sections cumulatively.

Table 1. Structured sub-dataset

Terms	Skills	Character	Communication	Interaction	Individuality	Temperament	Culture
Always	0	1	1	0	0	0	0
Business	3	1	0	0	1	0	3
Create	1	0	1	0	0	0	0
Creative	1	0	0	0	0	0	1
Depends	0	0	1	1	1	0	1
Development	0	0	1	0	0	0	1
Different	0	0	0	2	1	0	0
Environment	0	0	1	0	0	0	1
Field	1	0	0	0	0	1	0
Human	1	0	0	0	0	0	1
Important	1	1	0	0	1	1	0
Individual	0	0	0	1	0	0	1
Intelligence	0	2	2	0	0	2	0
Knowledge	1	0	0	0	0	1	0
Life	1	0	0	1	1	1	1
Love	0	1	0	0	0	1	0
Make	0	0	0	1	1	0	0
Matters	0	1	0	0	0	0	1
Natural	1	0	0	1	1	0	0
Needs	1	0	0	0	0	1	0
Numbers	0	0	2	1	0	0	0
Problem	1	0	1	1	0	0	0
Product	0	0	2	0	0	0	1
Right	2	1	0	0	1	0	1
Sell	0	0	1	0	0	0	1
Simple	0	0	1	1	0	0	0
Skills	2	0	0	0	1	0	0
Strong	0	0	0	1	0	0	1
Values	0	1	0	0	1	0	0
Without	0	0	1	1	1	0	0

4 Data Analysis and Visualizations

R and Python are employed to analyze questionnaire's data using popular IDEs, apps, and packages as R Studio, R Shiny, Shinyproxy and their Server versions. The following visualizations are about two respondents, A and B, as a case study example for a Web Development team context. For this case, authors have applied team members-based team development analysis methodology [60], where in this particular case, the respondent A did belong to a creative subgroup while respondent B was in a developers' subgroup.

Like explained at the previous section, a dataset consists of the respondent's answers without numbers, punctuation, grammatical prepositions, and a collection of stop-words is analyzed and visualized for interpretation, based on the frequency or the weight of each term. The type of visualization which has been chosen to depict the text analysis is the wordcloud. The word clouds present the significant ones words with enhanced fonts and closer to the center of the vacuolation. While, moving gradually towards the periphery of the cloud, the remaining less significant terms appear in smaller sizes. It is named total wordcloud because it uses no clustering.

The left side of Fig. 1 depicts the Total WordCloud with word weighing using TF-IDF Technique, which is a common statistical tool for normalization in information retrieval and text mining. Then the right side of Fig. 1 presents a clustered wordcloud of the same dataset, for respondent A, using word weights. Meaning that the wordcloud is determined separately for each section. Therefore, the clustered wordcloud is being created by splitting the data in seven datasets which represent the respondent's answers at the seven sections of the questionnaire. The coloring shows the frontiers of Temperament, Individuality, Interaction, Communication, Culture, Character and Skills.

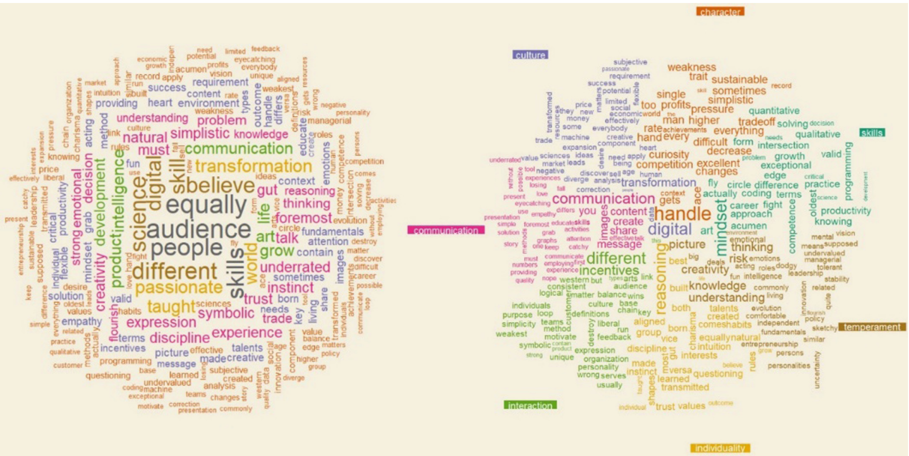

Fig. 1. Total wordcloud (left) & respondent a clustered wordcloud (right)

The bar plot at Fig. 2 shows the total wordcloud terms with the biggest weights, which are: **Audience, Equally, People, Skills, Different, Science, Believe, Digital,**

and Passionate. Therefore, respondent A presents a people-centric profile with interests in science and skills development. Moreover, Fig. 2 shows the bar plot of the clustered wordcloud terms with biggest weights: **Handle, Different, Reasoning, Mindset, Digital, Art, Communication, Intelligence, Incentives, and Emotional**.

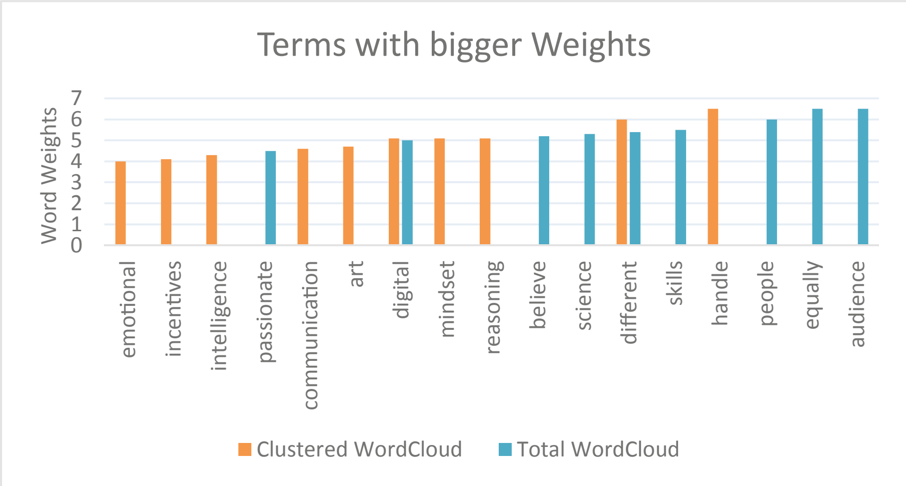

Fig. 2. Word weights for the total and the clustered wordcloud of respondent A

Figure 2 provides the respondents talent fingerprint for HR, which can be a critical factor in the hiring process and/or team development. In the example, the respondent presents a clear inclination in people-centric terms. On another hand, human mindset and talent are not set in stone, hence managers should approach them as sign of potential. In practice, by comparing these two types of wordclouds, the total and clustered one, we come up with two interpretations of the same dataset. The total wordcloud is more people-centric because of the most weighted words, which are the ones that the respondent preferred the most, focus on **Audience, People, Skills, Belief, Passion, Life, Art, and Emotion**. While the clustered wordcloud presents, also, a managerial and market-oriented side using terms as **Handle, Digital, Reasoning, Mindset, Communication, Intelligence, and Incentives**. Therefore, the big picture of their talent fingerprint is people-centric, but with a closer look, there is business thinking, too.

In conclusion, as the most preferred terms show, the total wordcloud of respondent B (at the left side) depicts a strong business and product development profile. This is an important piece of information for HR experts and talent hunters [56]. People's inclinations are the fields and directions in which they would be more productive, cooperative, and creative, both as human beings and professionals. Figure 3 also presents the clustered wordcloud of respondent B (at the right side) with weighting. Consequently, clustering brings at the surface new aspects of respondent's profile. At this case, respondent B emerges with an engineering side.

Fig. 3. Total wordcloud (left) & respondent B clustered wordcloud (right)

Figure 4 shows the respective bar plot with the most weighted words of the respondent's dataset. By these means, visualization of their inclinations is important in orientation, development, coaching and management. Their most weighted words from the total wordcloud, as Fig. 4 shows, are: **Product, Life, Skills, People, Market, Intelligence, Different, Science, Integrity and Believe**. Additionally, their most weighted words from the clustered wordcloud are: **Solving, Communication, Skills, Different, Acumen, Language, Programming, Competition and Data**.

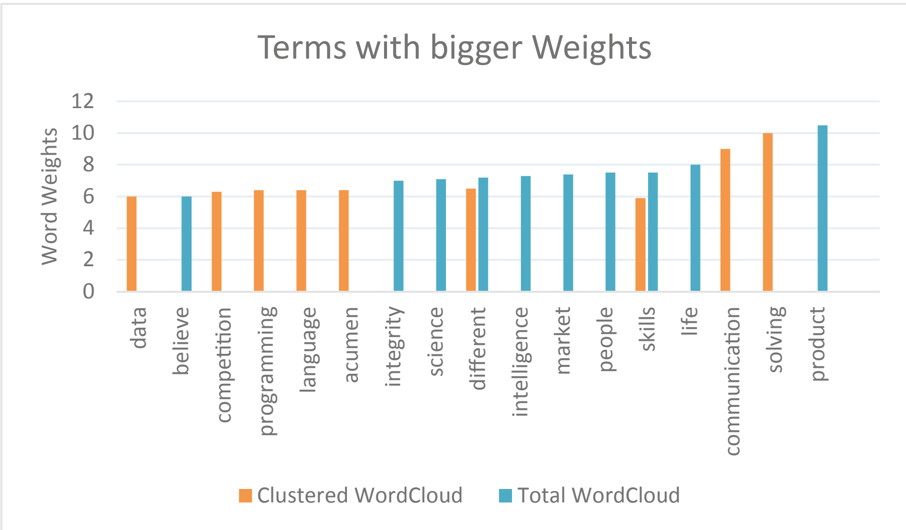

Fig. 4. Word weights for the total and the clustered wordcloud of respondent B

In addition to the total wordcloud, the clustered one depicts that respondent B presents a business profile but with an engineering flair, too. In a word, wordclouds with proper text analysis based on weights provide a pictorial way to present a general view of talent profiling and mindset mapping. The outcome is qualitative, and it depends largely on the questionnaire and the HR specialist.

5 Population in Group

Popularity is a measure which represents the number of respondent's answers which are identical with other participants. All the analysis and visualizations of popularity have been implemented with R opensource tools. It is worthy to note that on popularity analysis there is no text analysis or natural language processing because it focuses solely on identical answers. Figure 5 shows such a visualization for the candidate 14. Their responses are visualized and compared, for each section of the questionnaire, to the respective ones of a group of 14 participants. The answers which are unpopular within a group imply that only a few other participants have made the same choices at this section of the questionnaire.

LP stands for answers of low popularity, MP for medium popularity and HP for highly popular answers. LP answers are those which are not preferred by more than 20% of the group, MP answers are those between 20% and 50% and HP answers are those which are chosen by more than 50% of the group participants. Just a look is enough to conclude that the candidate's answers are quite popular in the group for the Communication and Culture sections. Also, there seem to be polarized answers in the Interaction section, always considering the choices of the group. Consequently, at this type of analysis, we visualize a candidate's popularity per section in a specific group of people.

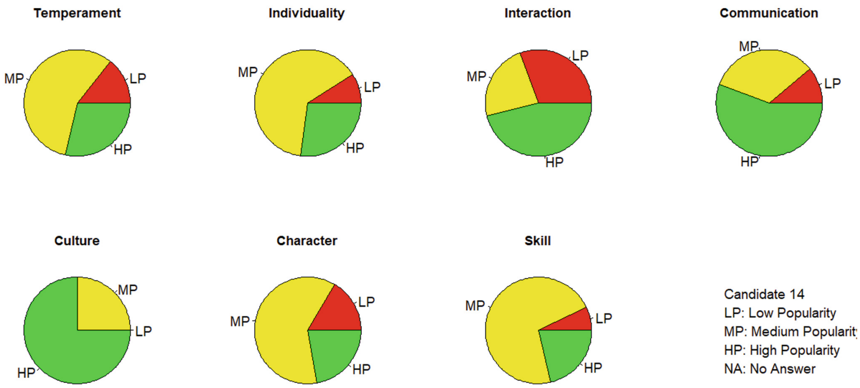

Fig. 5. Popularity and polarization

Figure 6 visualizes the answers of all respondents of the group without splitting them into sections. This visualization shows the most popular candidates among the group. Popularity, again, is the number of the identical answers in total i.e. how many answers were identical among participants at the Brainstorming Type Questionnaire.

Candidates 5 and 8 are among the most popular respondents in this group, while candidate 1 was most unpopular which may imply that he is just an outlier. Certainly, candidate 1 is a misfit to that group because picture 13 shows that his Low Popularity (LP) area is almost 50%, while his LP and MP areas combined are almost 80%, implying that his answers are quite unpopular in the group.

Furthermore, as the following chapter shows, that claim is also verified with the heatmap analysis, at Fig. 6, because the column of candidate 1 shows low similarity score with all the other candidates. Almost all his similarity pairs are colored by deep blue or green. However, as it has been already noted, a misfit team member may be the one it is needed for team growth and development. Therefore, outliers must be analyzed more so as to reach solid conclusions.

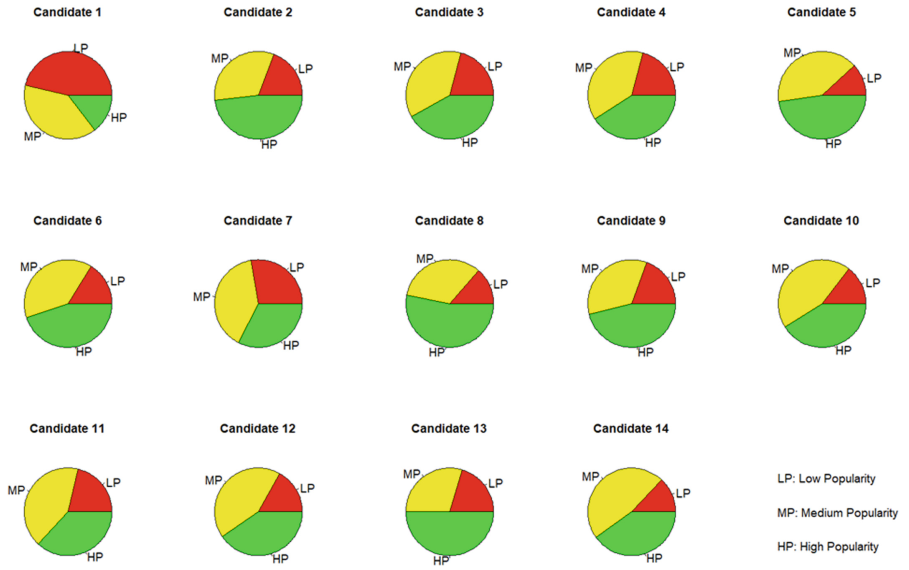

Fig. 6. Popularity in the group

6 Similarity in a Group

Similarity is different than Popularity because in this case it is expressed by the Power Predictive Score which is a statistical method. Therefore, this analysis does not focus on identical answers but on similar patterns. Consequently, Similarity includes text analysis but without frequencies or weights. The input is the term patterns for a single candidate which is compared to all other members' term patterns of the group. Code Section 4 presents a sample of the R code which has been used for the implementation of the following heatmap graph.

Code Section 4. Heatmap Implementation

```
            Heatmap.R                                   #For data mining and normalization
vals <- readLines("results.txt")                        #Get the results of Power Predictive
Score (PPS)
splited <- str_split(vals[1:length(vals)], pattern = " ")
unl <- unlist(splited)
df <- data.frame(splited)                               #Generate data frame with all members
colnames(df) <- c(1:length(splited))
matr <- as.matrix(df)                                   #Transform it to a matrix
for(i in 1:nrow(matr)){
for(j in 1:ncol(matr)){
if(i != j){
            matr[i, j] <- as.numeric(matr[i, j]) * 2.08
            }           }           }

heatmapFuncReactive <- reactive({                       #Reactive Programming for
Visualization
      source(file = "heatmap.R")
            })
            output$ppsHeatmap <- renderPlot({                        #Plot the Heatmap
            heatmapFuncReactive()
            levelplot(matr[1:input$heatmapSlider,
1:input$heatmapSlider], col.regions = viridis(100),
               xlab = "Features", ylab = "Predictors")
            }, width = 750, height = 750 }
```

The results.txt file is the output of ppscore, a Python implementation of the Power Predictive Score (PPS) [58]. The PPS is asymmetric and data agnostic that may detect linear and/or non-linear relationships between two columns. The PPS ranges from 0, implying no predictive power, to 1 which is perfect predictive power. It is important to note that it may be used as an alternative to the correlation (matrix).

Practically, with PPS, column x predicts column y and vice versa.

- A score of 0 means that x cannot predict y better than a naïve model.
- A score of 1 means that x can perfectly predict y.
- A score between 0 and 1 declares the predictive power the given model achieved compared to the baseline model.

At this case, PPS employs a decision tree which is a learning algorithm with the following properties:

- It can detect any non-linear bivariate relationship
- Satisfying predictive power in a wide variety of use cases
- It is a robust model which can handle with outliers and overfitting.
- It can be used for classification and regression.
- It is faster compared to other algorithms.

Moreover, at this project Correlation cannot be used because it works only for numerical data with linear relationships. However, in this word analysis there are columns with categorical data. Additionally, the PPS detects every relationship that the correlation does. Thus, PPS matrix can detect and analyze linear or nonlinear patterns in categorical data. Lastly, the predictive power score can be used to discover good predictors at target column which is useful information in industrial and commercial applications.

Figure 7 depicts a heatmap with 14 individuals as a group. PPS (Power Predictive Score) [45, 46] is being used to match individuals based on their responses at the questionnaire. The color scale from Blue to Yellow is translated as low to high Similarity, respectively, for each pair of candidates. Rows represent features and Columns the predictors, meaning that high scores imply accurate predictions by using features as a reference and vice versa. But as it has been already noted the outcome is not necessarily symmetrical.

For example, the pair (2,11) presents high similarity while the pair (3,7) low similarity. Implying that the first pair of candidates, number 2 at x axis as feature, and number 11 at y axis as predictor, have similar mindset. Moreover, the candidates 1 and 3 are outliers in that group, meaning that they do not match with other members in this group.

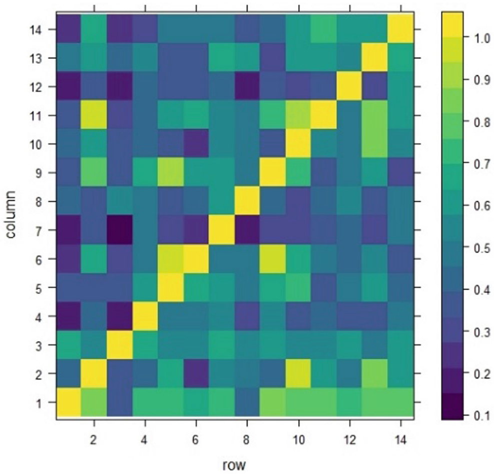

Fig. 7. Predictive score heatmap

In fact, an important fact to keep in mind in Talent Management [20] is the reality that the indicators have multiple interpretations, but they can still be more than a useful map for Team Leaders, Managers and Directors [53, 57]. People management depends on human judgement and this is not a cliché [54, 55]. However, data science tools provide critical information and neutrality on talent profiling and assessment. Additionally, comparison of profiles returns information for team development. In teams, commonly, there are similar, complementary, and irrelevant profiles. Furthermore, time to time, outliers in teams and companies make a difference.

Being an outlier means nothing for one's capacity as an individual, but it's sign that he may play a different role in the group or not, even, participate at all, like an intrapreneurs with special role in organizations. A role where they provide a special input for team growth and development. Also, an outlier in 'team sense' might be a highly talented evaluator or progress monitor for the team as he takes different point of views into discussion table, what the team itself in general does. Lastly, non-similarity can be interpreted it as complementarity in some cases, which is a basic characteristic for exceptional teamwork [42, 43].

7 Discussion

A profiling tool for talent assessment [25, 51] and management should be approached as utility [47], since performance, which is what really matters, can be improved only by employing the right metrics. Implying that it must add value, in real terms, on management, administration, teams and, above all, individuals [30]. Qualitative analysis tools can be used as a guide map, but they cannot replace human judgement because emotional intelligence, which is expressed through vision and creativity, is a human trait. We use IT tools to gather and analyze information but not to make executive decisions.

Practically, individual assessment is data analysis based on the responses of each single candidate. This research has shown that with proper interpretation of respondents' answers, one can unfold their mindset and values through the brainstorming type questionnaire. By its nature, this approach is not precise but abductive which is what really matters in profiling and orientation. Analytics frame respondents' preferences, as well as categorize and match them with other respondents. The outcome is the orientation of individuals and/or teams which has been implemented by word weighting of their options and their similarity score in a group.

Moreover, group analysis is also important, especially, in team development [26, 48]. Most companies need HR insights for teamwork, evaluation, coaching and personal development [36, 37, 40]. Grouping is all about personality match, similarity, and complementarity [41, 42]. Despite the technical importance of data analysis, talent profiling must not be downgraded to a technicality [34, 35].

Finally, in regard to team development, research must be extended beyond similarity so as to bring more solid results. As it is noted, team members' profiles can be, also, complementary which is of high importance in business and product development because teams need people with different strengths and mindsets. However, complementarity is a more challenging issue than similarity from a research point of view.

8 Conclusions and Future Research Recommendations

This research was focused on individual and group analysis creating a conceptual framework [7] employing a method which visualizes an individual's mindset using a brainstorming questionnaire and text analysis. The outcome has shown that wordcloud visualizations depict differences in mindsets and career orientation. Moreover, Popularity is a single measure which presents how popular a member is in a group. On the other side, Similarity score unveils the similar mindsets between candidates and/or members of a group. Should the Power Predictive Score be high, with 1 representing the perfect predictive power, it would imply that there is a pattern at the datasets of two members. However, as it has been noted at the discussion section, Complementarity is also important for group analysis, especially, for team development. Therefore, future research must include similarity and complementarity so as to provide more information for group members.

Lastly, the coarse and fine focus is, also, on a future research framework in Qualitative Analysis and HR product development [55]. Certainly, the right balance between course and fine focus returns the best outcome on (TP) True Positives and (FN) False Negatives [52]. However, as it is known, empirically human resources [20] is a long-term game which needs time and consistency to be tested and validated. It is a case study of long-term investment which pays off once the management gets the right balance [49, 50, 56].

Additionally, the relevance of the most frequent or weighted words at wordcloud visualizations is a point of interest. At large or specific datasets, Relevance based clustering returns information for respondents and candidates.

HR digital transformation, known as HR 4.0, needs quality and quantity to improve hiring process and productivity. At the moment, this talent assessment tool can be functional for small groups. Therefore, future research could involve the development of KPIs which can rank candidates providing HR specialists with specific metrics and not only visualizations. For instance, a similarity analysis tool could be developed based on word weights for group analysis and profiling. Hence, it would be easier to rank candidates employing specific indicators.

Important part of future research is the automation of the process. Meaning that the HR departments would have at their disposal, after the analysis, a shortlist which may be used for interview calls. This automation should be depended on certain KPIs to match candidates with certain positions' profiles or, even, evaluate unsolicited applications. Those KPIs should focus on finding the best fit for teams and positions. On other side, building a list with candidates for particular roles is, also, important for growing companies. Consequently, this talent profiling tool could contribute to the trend of HR 4.0 with further development towards full digitalization of HR processes. For example, should a candidate present a people-centric profile and, at the same time, appear to have a quite similar profile with a company's salesmen group, it would imply that they will be suitable for such a role. Hence, building two KPIs on talent profiling and similarity would provide, instantly, HRs with a robust solution for candidate shortlisting at some job categories.

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