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The Best Workplace According to an Artificial Intelligence Algorithm

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Abstract

This work opens an avenue for organizations to immediately understand why their employees want to leave for other opportunities in the job market and act in time, taking precise internal measures to avoid losing talented personnel that consumed substantial investments in training. Data were collected from two well-known websites over nine months, gathering a sample of 1,307 employee reviews of companies. The reviews refer to ten of the largest global organizations, often cited in recent articles as companies with outstanding organizational agility. One by one, the sample reviews were submitted to artificial intelligence (AI) algorithm that conducted a sentiment analysis. This procedure offered a ranking of organizations based on how happy employees work there, overriding other negative feelings, such as fear, sadness, and anger. The analysis results showed that Google was the place where people feel happiest. Other dimensions were identified and inspired reflections, such as the employees' joy of belonging when comparing the current and former employees and the dimension of the best country to work in when the employer is a global organization. The study allowed us to infer which career position workers are more likely (positive sentiment) or less likely (negative sentiment) to commit to the organization. We believe that AI will emerge as an important tool in structuring organizational agility, allowing the concept of a great workplace to be developed and assessed in real-time. This research is aligned with studies that recognize the organization as a living organism where people are the main actors. We understand and hope that organizational processes will be revisited and will consider this new avenue, in due course, paving the way for the integration of external variables, such as emotions, to support human resources internal measures aimed at reversing low engagement and loss of talents.

Keywords

Sentiment analysis, Organizational agility, Best workplace, Artificial intelligence, Information technology.

Introduction

This proposal demonstrates in a practical way how social alignment is important for responding to the desires of employees, who in the act of wanting to be heard, seek social media to vent about adverse situations in their organizations. On the other hand, the organization must develop or improve its internal alignment standards that allow a prompt response to its employees on these social media, reaffirming the humanity of its management and the retention of talents.

This research proposes something similar to the organization Great Place To Work (the acronym GPTW is used in this article to refer to the organization and the concept). This organization has extensive experience in research and diagnostic tools to assess organizational climate and collect the employees' perceptions of the company, building a ranking of best workplaces. This study also seeks to identify the best workplaces, but we did not use the research methods applied by the GPTW due to the impossibility of access to companies and limited time and resources. We call our attempt GPTW_AI since we refer to the concept GPTW and use an artificial intelligence (AI) algorithm to analyze reviews that current and former employees wrote about their experiences in the organizations (i.e., the employees' perceptions). Also, like the organization GPTW, we use our analysis to build a ranking of the best workplaces. The analysis of employee reviews led to three questions stated below and addressed in this article. The first question **(Q1)** was, "how do organizations use employee reviews on websites?" The second question **(Q2)** was, "is it possible to use sentiment analysis to rank a company using GPTW_AI?" Finally, the question **(Q3)** was, "could the organization use sentiment analysis to subsidize human resources internal measures that respond to changes in the political-social and technological contexts?"

Despite the general understanding of sentiment analysis, there is no research, to the best of our knowledge, addressing its use to measure the relationship between people's emotions, organizational agility, and the concept of GPTW. In our view, sentiment analysis will become a common method in netnographic and dialectic studies conducted in real-time, as in studies with human beings. This research demonstrates this view by adopting an AI algorithm to read each employee review of ten global companies. As better described in the following sections of this article, these reviews formed a sample of 1,307 written and published on the websites Glassdoor and Indeed between 2019 and 2022. Data collection was manual and did not use an application programming interface (API), a procedure adopted to assess the algorithm's interpretation of each typed text. Future studies can use automation and encompass as many reviews as desired.

This study shows the emotions of anger, disgust, fear, sadness, and joy as assessed by the AI algorithm. However, the discussion presented here will focus on the emotion of joy, adopted as an indicator of workplace quality, to rank the companies that were the object of the reviews analyzed. This work does not align with studies on the AI's recognition or ideographic unfolding, and it does not defend how the algorithm transforms texts into emotions. However, we studied and used references on the subject [9-26 of Table 2].

Literature review

The literature review was structured to obtain a top-down view of the authors and categories that permeate this work. It starts with the areas, subareas, theoretical lenses, and references. The areas that underlie this research are organizational agility, research assessment, and sentiment analysis (Tables 1 and 2). The theoretical lenses presented in this structure were fundamental for each area. However, not all theories supporting the discussion of results presented in this article were mentioned, as this would require more comprehensive content, extrapolating the page limit required.

Area	**Subarea**	**Theoretical lenses**	**References**
Organizational agility	Operational alignment	Social Capital	1. Wagner, H.T., Beimborn, D., & Weitzel, T. (2014)
	Strategic alignment e Strategies for theorizing	Meta-analysis	2. Gerow, J.E., et al. (2014); 3. Yoshikuni, A.C. et al. (2018) 4. Langley, A. (1999)
	Competitive perspective	Mediation model	5. Tallon, P.P., & Pinsonneault, A. (2011)
	Alignment between business and IT	Social dimension Social Alignment	6. Reich, B.H., & Benbasat, I. (2000) 7. Zhou, J., Bi, G., Liu, H., Fang, Y., & Hua, Z. (2018).
Research evaluation	Qualitative research	Criteria for conducting research	8. Pozzebon, M., & Petrini, M. (2013)

Table 1. Literature Review on Organizational Agility and Research Assessment

Area	Subarea	Theoretical lenses	References
Sentiment analysis	Exploration	Meta-level Writing expressions Libraries Statistics	9. Canuto, S., Gonçalves, M.A., & Benevenuto, F. (2016)
	Measurement		10. Dodds, S.P., & Danforth, C.M. (2017)

	Textblob Documentation	Opinion Mining Cultural	11. Loria, S. (2018)
	Statistics for NLP		12. Manning, C. D., & Hinrich, S. (2000)
	Sentiment		13. Pang, B., & Lee, L. (2008)
	Emoticon styles		14. Park, J., Barash, V., Fink, C., & Cha, M. (2013)
	Twitter	Corpus	15. Park, A., & Paroubek, P. (2010).
		Humor	16. Bollen, J., Mao, H., & Zeng, X. (2010)
		Significant events	17. Sykora, M.D., Jackson, T.W., Iboro, A.O., & Iboro, S.E. (2014)
		Sentiment	18. Tumasjan, A., Sprenger, T.O., Sandner, P.G., & Welpe, I. (2010)
	Recognition Standard	Machine learning	19. Bishop, C. M. (2006)
			20. Hasan, A., Moin, S., Karim, A., & Shamshirband, S. (2018)
	Words in English	Affective norms	21. Bradley, M.M., & Lang, P.J. (1999)
	Words in Portuguese		22. Kristensen, C. H, Gomes, C. F. A., Justo, A.R., & Vieira, K. (2011)
	Classification	Distance supervision	23. Sahni, T., Chandak, C., Reddy, N., & Singh, M. (2017)
		Resource engineering	24. Scott, S., & Matwin, S. (2000)
	Sentiment Strength Detection	Social web	25. Mike, T. (2013)
	Starting the AI Journey		26. Munoz, M. J. & Matteo, D. (2021)

Table 2. Literature review on sentiment analysis

Theoretical positioning

This research is oriented by data and theoretical lenses, adopting a mixed approach. In the initial phase, theoretical lenses were used to support the concepts of sentiment analysis [13 and18] and organizational agility [1, 2, 3, and 5], obtaining a structure to guide the search for specific constructs to answer the three research questions.

Methodology

The netnographic approach was used to collect secondary data from web content in different data sources. The analysis units focused on a previously defined group of companies and individuals linked to them. The declaration of confidentiality and data protection was not required since the study did not use personal (or classified as sensitive) data and they were collected from open-access websites. Table 3 demonstrates the method of data collection and analysis used to support this research.

Research method	Data collection
Netnography	Structured and semi-structured
	Web content,
	Secondary data and Text analysis

Table 3. Summary of research strategy and data collection

Data collection

Data sources

The definition of data sources offering employee reviews was essential for this study. The use of the websites Glassdoor and Indeed – platforms offering employee reviews about companies – facilitated since it was not necessary to create research instruments, saving time and avoiding other biases, low number of responses, and limit in the number of companies assessed.

Questionnaire

This phase of the study aimed to build the basis for quality information. While developing this research, we had the opportunity to present the research assumptions and design to many master's and Ph.D. students and professors from an important business school. Throughout this process, several questions were asked about the research, in particular, about the ability of the algorithm to recognize Brazilian Portuguese – our working language. Such interventions motivated us to generate a questionnaire with questions and guidelines for data collection to ensure maximum quality. The questionnaire was compiled from an extensive list of questions and guidelines we called items of a quality questionnaire.

Items of a quality questionnaire

The items we observed in the questionnaire to formulate questions and guidelines to increase the quality of the data collected were the databases, languages, data structure, quantity of data, companies reviewed, period of data, number of lines typed, characteristics that invalidate the reviews, text to be placed in empty fields (null), formulas and formatting to be used, emotions, the definition of the sentiment analysis algorithm, design of the extraction, transformation and load stage for BI software (Tableau and PowerBI).

The questionnaire, partially described in Table 4, follows the main question in the general guidelines questions column. Next, several questions are asked (second column) until the doubts related to that item are exhausted. Finally, the column with the guidelines and execution presents what should be followed during data collection. Table 4 shows one of the items, 'language' [11,15,21 and 22], to clarify how the questionnaire was created to guide data collection.

General guideline questions	**Questions and categories Concepts/Ideas**	**Guidelines and Execution**
1. **Which language** should be used for the sentiment analysis algorithm?	**Language analysis**: 1.1 Would it be appropriate to test the algorithm with the languages found in the data sources? 1.2 If the algorithm has multi-language libraries, would it be easier to run it directly in the reviews, regardless of the written language? 1.3 If we run the algorithm in the same text written in different languages, would there be divergences in the sentiment analysis? 1.4 What would be the best language to run the algorithm?	1. We collected one review written in each language found on the websites used as data sources: Portuguese, Spanish, French, German, and English.

Table 4. Questions to establish the data collection guidelines (Language)

The other items of the quality questionnaire mentioned above were submitted to the same guidelines as in Table 4, resulting in adequate decisions to guarantee the quality of the data collected. This procedure will not be presented here to keep the article at a reasonable length.

Data structure and practical execution

We collected the following data:

- Database (name of data sources: Glassdoor or Indeed);
- Organization (name of the company reviewed);
- Review date;
- Time in the company (time that the employee works or worked in the company);
- Status (current or former employee);
- Position (position held);
- Country, state, and city;
- Numerical rating (1 to 5-star rating);
- Review (general comment the employee wrote about the company)
    - Written review – Pro-company (for sentiment analysis)
    - Written review – Against the company (for sentiment analysis)
    - Written review – Recommendation to the CEO (for sentiment analysis)

The selected organizations

Ten companies were selected from a universe of sixteen identified in various articles on digital transformation and organizational agility. Authors cite these companies as organizations that started the path of digital transformation and were the inspiration for this study.

Table 5 shows the number of employee reviews of each company. The column 'Total' is the sum of the reviews of the two websites. The column 'Our collection' is the number of reviews typed, forming the data structure to submit the algorithm.

		data source records			
	Companies	Glassdoor	Indeed	Total	Our collection
1	Amazon	104,273	78,183	182,456	154
2	Apple	27,513	10,653	38,166	166
3	Cisco	25,963	6,043	32,006	143
4	Facebook	9,214	643	9,857	122
5	Google	28,044	4,010	32,054	158
6	IBM	81,939	31,101	113,040	139
7	Microsoft	37,202	7,328	44,530	100
8	Oracle	38,408	6,435	44,843	71
9	SAP	22,377	2,603	24,980	147
10	Walmart	87,017	230,623	317,640	107
		461,950	377,622	839,572	1,307

Table 5. Companies and reviews on Glassdoor and Indeed

All companies in Table 5 have more than 10,000 employees with annual revenue above 10 billion dollars and are present in several countries.

The reviewers' employability situation

Table 6 presents the number of reviewers (current and former employees) of each organization. More current than former employees are reviewing the companies, indicating the employees' desire to be heard.

Situation	Amazon	Apple	Cisco	Facebook	Google	IBM	Microsoft	Oracle	SAP	Walmart	**Total**
Current employee	102	83	89	84	94	74	44	29	104	47	**750**
Former employee	52	83	54	38	64	65	56	42	43	60	**557**
Total	**154**	**166**	**143**	**122**	**158**	**139**	**100**	**71**	**147**	**107**	**1307**

Table 6. Reviewer situation

Characteristics that invalidate the reviews

When the data structure was finalized, we observed that many reviews missed important data for the research, such as country, state, and city. Therefore, all reviews without these characteristics were excluded.

Text included in empty fields so they did not appear as null

Much information collected was recorded as confidential or incomplete, such as position, current employee, and time in the company. In the treated database, texts were named 'unknown' or 'anonymous.' Thus, when manipulating data for reports and graphs, it was possible to filter out incomplete records that did not influence the result of the sentiment analysis.

Formulas and formatting used

The sentiment analysis results were considered as the algorithm generated them, i.e., as percentages with two decimal places. Therefore, we did not have to change the type of data, and the numbers were presented in averages.

The Algorithm

This research used an algorithm of a company that specialized in artificial intelligence (by the time we ended this study, we had not been granted authorization to disclose the company's name). The company also allows access to its algorithm via API (Application Programming Interface). However, we did not use API in this study.

Table 7 presents a preview of the emotions the algorithm analyzed. The numbers in this table are consolidated averages of the 1,307 reviews.

Company	Sentiment Mix	Joy	Fear	Sadness	Disgust	Anger
Google	50%	60%	6%	10%	6%	5%
Cisco	42%	54%	7%	14%	8%	7%
Microsoft	44%	54%	7%	12%	7%	6%
SAP	44%	53%	5%	9%	5%	5%
IBM	41%	53%	6%	13%	5%	6%
Oracle	44%	53%	6%	11%	6%	6%
Apple	38%	52%	9%	16%	8%	8%
Facebook	40%	52%	5%	15%	7%	7%
Walmart	32%	51%	12%	21%	12%	11%
Amazon	32%	48%	12%	18%	11%	8%

Table 7. Averages of the sentiments analyzed

The column 'mix' in Table 7 represents an average of all other columns. Although it presents relevant data, it will not be used as a guide for this work since it synthesizes all emotions, i.e., it is not fit to represent a great place to work. The other columns are averages of other individual emotions obtained by the algorithm.

The search for reviews by country was random. During the data collection, we identified opportunities for further analysis when mining a larger amount and more homogeneous reviews of companies in each country, which can be carried out in future studies. These analyses may provide answers for companies interested in the subject – for example, if an organization is willing to implement internal human resources measures in a specific location where the sentiment analysis identified that 'joy' is below the average compared with other countries.

Data analysis

The data analysis techniques discussed in this work were influenced by [4] visual mapping concepts to understand aspects of the temporal track strategy, i.e., the longitudinal importance of data within the organizational process. It was not possible to carry out an in-depth longitudinal analysis due to the insufficient number of records by date. However, it is possible to conduct such a research effort in the future.

It is worth mentioning that the research is embryonic. Therefore, data analysis can be conducted with other methods, and other data structures can be arranged to improve results.

Results

We observed numerous interesting results and focused on those that answered the research questions. We believe that the other insights can be explored in future work.

We answer each of the research questions objectively so they can be understood for possible reproductions by other researchers.

Q1: How do organizations use employee reviews on websites? **A1**: This work demonstrates how the organization can access employee reviews. We took a longer time than expected to mine the data and run the algorithm, and we identified that there are technical conditions for capturing data in real-time.

Q2: "Is it possible to use sentiment analysis to rank a company using GPTW_AI? **A2**: We believe that if the company considers that the emotion of joy obtained by the artificial intelligence algorithm is an important variable to measure how employees perceive the organization, this emotion may guide timely internal measures for talent management.

Q3: Could the organization use sentiment analysis to subsidize human resources internal measures that respond to changes in the political-social and technological contexts? **A3**: The research showed that the organization could collect data in real-time, understand the employees' emotions, and create internal human resources measures to reverse situations of loss of employees and credibility. Companies can monitor whether internal actions reflect externally in a positive way by constantly collecting data and updating this emotional dimension.

The best workplace according to an AI algorithm

When obtaining the final average of the emotion of joy (by the company), considering the two databases, we concluded that Google was the best workplace when using our GPTW_AI method, with 61% joy of belonging to the company (Chart 1).

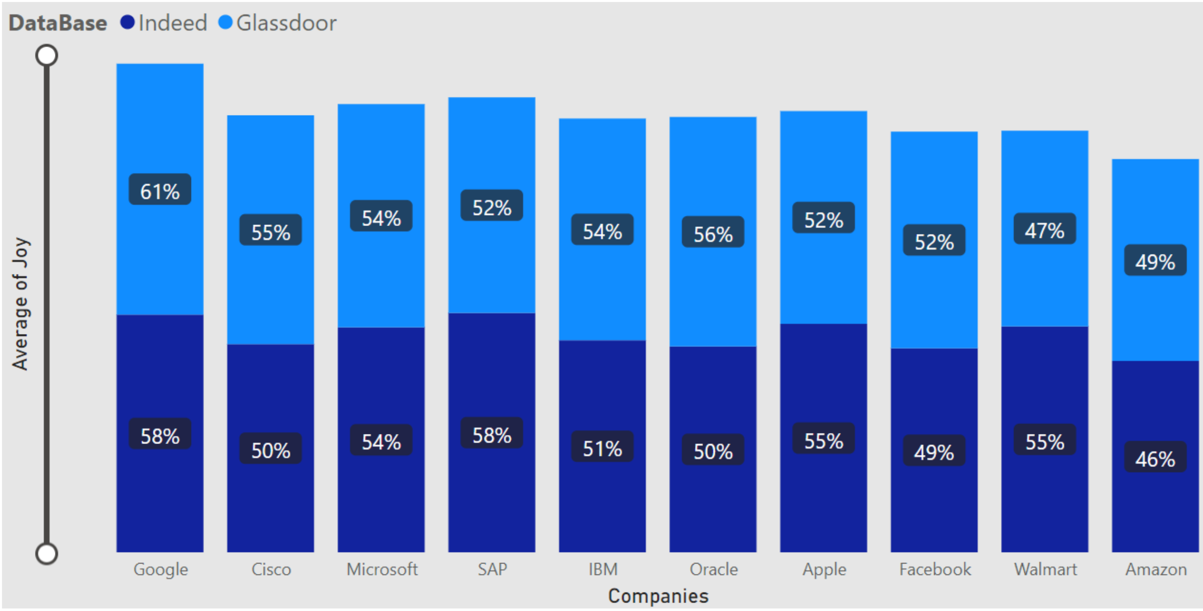

Chart 1. Average emotion of joy by database and company

Discussion

We thought initially that a large number of reviews should be analyzed to obtain a coherent result. Throughout the work, we observed that this was not necessarily true. However, if the study is oriented to a specific company, it would be interesting to consider more reviews and a longitudinal perspective. In our perception, the longitudinal study will be the most relevant in future research, considering the possibility of verifying the success of the company's internal measures over time.

This study can be an important contribution if the researcher wants to delve into other emotions, such as fear or sadness. Particularly, fear could be a work condition variable where stress pushes people to their limits and causes sick leave and dismissal. Other dimensions of fear could be considered, for example, workplace aggression, moral harassment, and other situations that could culminate in liabilities. Likewise, sadness could be a collective indicator of an unpleasant work environment for several reasons.

Many AI initiatives are observed in the literature, some of them successful, others a great failure. Also, many authors write on the subject to structure the concepts but rarely give practical ways to adopt AI. Our research has found a practical path any company can take to use AI. However, we recommend the steps cited by [26] as a safe guide to complete our work: 1. know your objective; 2. walk and do not run; 3. adopt a data culture; 4. set checkpoints, and 5. create multi-functional teams. These guidelines may not be suitable for all companies, but at the very least, they will help to minimize the risks of a project that could become very complex and with a high rate of failure.

Conclusion

Throughout the research, we observed that other dimensions of analysis could be measured, but this would have changed our approach. However, we encourage a study on the company's ability to respond to reviews with internal actions. This study dimension understands whether the organization has enough internal integrations to capture these reviews, respond to them, and generate internal changes to create a favorable environment for its employees. This modus operandi allows the company to evolve in a rank of best workplaces according to AI using our GPTW_IA method in all the countries in which the company operates.

We understand that this work opens new discussions on the use of AI, at least in the dimension of employee emotion and organizational responses. In this aspect, we consider that this work makes important contributions from the point of view of social alignment and organizational agility. There are countless possibilities of arrangements in administrative functions for surgical responses to internal and external pressures, in this case, from employees.

The main segment of companies studied were those with global operations, serving as a broad and generalizable sample. We emphasize that information technology companies are, in a way, the ones that could benefit the most from this study, as they hire specialized and scarce labor in many countries and, therefore, lack efficient controls to keep their employees engaged and happy.

We wondered why Google ranked first when adopting our GPTW_AI and found some indicators worth reporting. Since its inception in 1998, Google envisioned an organizational culture, unlike any other model. It strongly values collaboration with a university-like environment, encouraging constant research and development. Working in such an environment is also fun and exponentiates creativity and innovation. This justifies creating a specific position to strengthen this culture; the Chief Culture Officer (CCO).

As such, we consider this work a starting point for deeper discussions about how organizations will transform using AI to make and keep their employees happy. Although it was not explored in this work, many cases of people working from home were verified. It should be added that, possibly, remote work could indicate different feelings than those listed here, generating factors not yet experienced, except for the period of a pandemic – as nowadays, at the time we are writing this article. Certainly, future studies may focus on companies that have already announced this type of work as a new operating model, such as Twitter, and capture new insights into emotions.

References

1.Wagner, H.T., Beimborn, D., & Weitzel, T. (2014). How social capital among *information* Manage. Inf. Syst. 31 (1), 241–272. *technology and business units drive operational alignment and its business value*.

2. Gerow, J.E., Grover, V., Thatcher, J.B., & Roth, P.L. (2014). *Looking toward the future of it-business strategic alignment through the past*: a meta-analysis, MIS Q. 38 (4), 1059–1085.
3. Yoshikuni, A.C., Favaretto, J.E., Albertin, A.L., Meirelles, F.S. (2018). *The Influences of Strategic Information Systems on the Relationship between Innovation and Organizational Performance*. BBR - Brazilian Business Review, 15(5), 444-459.
4. Langley, A. (1999). *Strategies for theorizing from process data. Academy of Management*. The Academy of Management Review; 24(4); ABI/INFORM Global pg. 691.
5. Tallon, P.P., & Pinsonneault, A. (2011). *Competing perspectives on the link between strategic information technology alignment and organizational agility*: insights from a mediation model, MIS Q. 35 (2), 463–486.
6. Reich, B.H., & Benbasat, I. (2000). *Factors that influence the social dimension of alignment between business and information technology objectives*, MIS Q. 24 (1), 81–114.
7. Zhou, J., Bi, G., Liu, H., Fang, Y., & Hua, Z. (2018). *Understanding employee competence, operational IS alignment, and organizational agility – An ambidexterity perspective*. Information & Management (I&M) https://doi.org/10.1016/j.im.2018.02.002.
8. Pozzebon, M., & Petrini, M. (2013). *Critérios para Condução e Avaliação de Pesquisas Qualitativas de Natureza Crítico-Interpretativa*. In A. R. W. Takahashi (Ed.), Pesquisa Qualitativa em Administração: Fundamentos, métodos e usos no Brasil (pp. 51-72). São Paulo: Atlas
9. Canuto, S., Gonçalves, M.A., & Benevenuto, F. (2016). *Exploiting New Sentiment-Based Meta-level Features for Effective Sentiment Analysis*, WSDM'16, February 22–25, 2016, San Francisco, CA, USA. ACM. DOI: http://dx.doi.org/10.1145/2835776.2835821.
10. Dodds, S.P., & Danforth, C.M. (2017). *Measuring the happiness of large-scale written expression*: Songs, Blogs, and Presidents, Cornell University, https://arxiv.org/abs/1703.09774.

11. Loria, S. (2018). *Textblob documentation*, Release 0.15.1.
12. Manning, C. D., & Hinrich, S. (2000). *Foundations of statistical natural language processing*, ISBN 0-262-13360-l, Computational linguistics-Statistical methods, P98.5.S83M36 1999 410'.285-dc2. Second printing, 1999 Massachusetts Institute of Technology with correction.
13. Pang, B., & Lee, L. (2008). *Opinion mining and sentiment analysis*, Foundations and Trends in Information Retrieval, 2 (1-2), 1–135.
14. Park, J., Barash, V., Fink, C., & Cha, M. (2013). Emoticon Style: *Interpreting Differences in Emoticons Across Cultures*, Seventh International AAAI Conference on Weblogs and Social Media.
15. Park, A., & Paroubek, P. (2010). *Twitter as a Corpus Sentiment Analysis and Opinion Mining*, Proceedings of the International Conference on Language Resources and Evaluation, LREC 2010, 17-23, Valletta, Malta
16. Bollen, J., Mao, H., & Zeng, X. (2010). *Twitter mood predicts the stock market*, Cornell University, https://arxiv.org/abs/1010.3003.
17. Sykora, M.D., Jackson, T.W., Iboro, A.O., & Iboro, S.E. (2014). *Twitter-based analysis of public, fine-grained emotional reactions to significant events*. IN: Rospigliosi, A. and Greener, S. (eds). Proceedings of the European Conference on Social Media ECSM, University of Brighton, UK. Academic Conferences and Publishing International Limited, 540-548.
18. Tumasjan, A., Sprenger, T.O., Sandner, P.G., & Welpe, I. (2010). *Predicting Elections with Twitter*: What 140 Characters Reveal about Political Sentiment, Fourth International AAAI Conference on Weblogs and Social Media.
19. Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*, 1st Edition. Springer Science+Business Media, LLC.
20. Hasan, A., Moin, S., Karim, A., & Shamshirband, S. (2018). *Machine Learning-Based Sentiment Analysis for Twitter Accounts, Mathematical and Computational Applications* (MDPI).
21. Bradley, M.M., & Lang, P.J. (1999). *Affective norms for English words* (ANEW): Instruction manual and affective ratings. Technical Report C-1, The Center for Research in Psychophysiology, University of Florida.
22. Kristensen, C. H, Gomes, C. F. A., Justo, A.R., & Vieira, K. (2011). *Normas brasileiras para o Affective Norms for English Words*. Trends Psychiatry Psychother. 33(3):135-46.
23. Sahni, T., Chandak, C., Reddy, N., & Singh, M. (2017). *Efficient Twitter Sentiment Classification using Subjective Distant Supervision*, Cornell University.
24. Scott, S., & Matwin, S. (2000). *Feature Engineering for Text Classification*, Carleton University and the University of Ottawa.
25. Mike, T. (2013). Heart and Soul: *Sentiment Strength Detection in the Social Web with SentiStrength*, Statistical Cybermetrics Research Group, School of Technology, University of Wolverhampton, Wulfruna Street, Wolverhampton WV1 1SB, UK.
26. Munoz, M. J. & Matteo, D. (2021). *Starting the AI Journey: How to Make the Right First Steps*. California Management Review, Technology, Frontier.