JPB REVIEW
INTERNATIONAL JOURNAL OF PROFESSIONAL BUSINESS REVIEW
ISSN: 2525-3654
OPEN ACCESS

WORKPLACE PRODUCTIVITY THROUGH EMPLOYEE SENTIMENT ANALYSIS USING MACHINE LEARNING

Surbhi Saxena[A], Anant Deogaonkar[B], Rupesh Pais[C], Reshma Pais[D]

ARTICLE INFO	ABSTRACT

Article history:

Received 31 January 2023

Accepted 10 April 2023

Keywords:

Sentiment;
Employee Productivity;
Machine Learning;
Pandemic.

Purpose: The objective of this study was to analyze workplace productivity through employee sentiment analysis using machine learning.

Theoretical framework: A lot of literature is already published on employee productivity and sentiment analysis as a tool, but the study here is intended to address the issues in employee productivity post-COVID'19.

Design/methodology/approach: The authors have studied the relationship between sentiments and workplace productivity post-COVID- 19. Sentiments were captured from the text inputs given by seventy-two survey respondents from a mid-sized consultancy firm and correlated against the productivity scores. A machine learning model was developed using Python to calculate the sentiment score.

Findings: 98.6% of the respondents had a high productivity score, whereas 88.9% showed positive sentiments. The majority of the responses showed a positive correlation between positive sentiments and high productivity levels.

Research, Practical and Social Implications: The study paves way for identification of action plan for productivity enhancement through sentiment analysis.

Originality/Value: No previous work on employee productivity using sentiment analysis is done till now.

Doi: https://doi.org/10.26668/businessreview/2023.v8i4.1216

PRODUTIVIDADE NO LOCAL DE TRABALHO ATRAVÉS DA ANÁLISE DE SENTIMENTOS DOS FUNCIONÁRIOS USANDO O APRENDIZADO DE MÁQUINA

RESUMO
Objetivo: O objetivo deste estudo foi analisar a produtividade no local de trabalho por meio da análise de sentimentos dos funcionários usando aprendizado de máquina.
Estrutura teórica: Já existe muita literatura publicada sobre a produtividade dos funcionários e a análise de sentimento como uma ferramenta, mas o estudo aqui pretende abordar os problemas da produtividade dos funcionários pós-COVID'19.
Design/metodologia/abordagem: os autores estudaram a relação entre sentimentos e produtividade no local de trabalho pós-COVID-19. Os sentimentos foram capturados a partir de entradas de texto fornecidas por setenta e dois entrevistados de uma empresa de consultoria de médio porte e correlacionados com as pontuações de produtividade . Um modelo de aprendizado de máquina foi desenvolvido usando Python para calcular a pontuação de sentimento.

[A] *Assistant Professor, School of Management, Graphic Era Hill University, Bhimtal, Uttarakhand. E-mail: surbhisaxena@gehu,ac,in Orcid: https://orcid,org/0009-0007-4008-1414*
[B] *Assistant Professor, Department of Management Technology, Shri Ramdeobaba College of Engineering and Management, Nagpur. E-mail: deogaonkara1@rknec,edu Orcid: https://orcid,org/0000-0003-1999-0027*
[C] *Associate Professor, Department of Management Technology, Shri Ramdeobaba College of Engineering and Management, Nagpur. E-mail: paisrs@rknec,edu Orcid: https://orcid,org/0000-0003-0789-5110*
[D] *Assistant Professor, Department of Humanities, Priyadarshini College of Engineering, Nagpur. E-mail: reshmapais@gmail.com Orcid: https://orcid.org/0009-0001-4298-5747*

Resultados: 98,6% dos entrevistados tiveram uma alta pontuação de produtividade, enquanto 88,9% mostraram sentimentos positivos. A maioria das respostas mostrou uma correlação positiva entre sentimentos positivos e altos níveis de produtividade.
Implicações de pesquisa, práticas e sociais: O estudo abre caminho para a identificação de um plano de ação para melhoria da produtividade por meio da análise de sentimento.
Originalidade/Valor: Nenhum trabalho anterior sobre a produtividade dos funcionários usando análise de sentimentos foi feito até agora.

Palavras-chave: Sentimento, Produtividade do Empregado, Machine Learning, Pandemia.

PRODUCTIVIDAD EN EL LUGAR DE TRABAJO A TRAVÉS DEL ANÁLISIS DEL SENTIMIENTO DE LOS EMPLEADOS MEDIANTE EL APRENDIZAJE AUTOMÁTICO

RESUMEN
Propósito: El objetivo de este estudio fue analizar la productividad en el lugar de trabajo a través del análisis de sentimientos de los empleados utilizando el aprendizaje automático.
Marco teórico: ya se ha publicado mucha literatura sobre la productividad de los empleados y el análisis de sentimientos como herramienta, pero el estudio aquí tiene como objetivo abordar los problemas de la productividad de los empleados después de COVID'19.
Diseño/metodología/enfoque: los autores han estudiado la relación entre los sentimientos y la productividad en el lugar de trabajo después de la COVID-19. Los sentimientos se capturaron a partir de las entradas de texto proporcionadas por setenta y dos encuestados de una empresa de consultoría de tamaño medio y se correlacionaron con las puntuaciones de productividad. . Se desarrolló un modelo de aprendizaje automático utilizando Python para calcular la puntuación de sentimiento.
Hallazgos: el 98,6 % de los encuestados obtuvo una puntuación de productividad alta, mientras que el 88,9 % mostró sentimientos positivos. La mayoría de las respuestas mostraron una correlación positiva entre sentimientos positivos y altos niveles de productividad.
Implicaciones de investigación, prácticas y sociales: el estudio allana el camino para la identificación del plan de acción para mejorar la productividad a través del análisis de sentimientos.
Originalidad/Valor: Hasta ahora no se ha realizado ningún trabajo previo sobre la productividad de los empleados mediante el análisis de sentimientos.

Palabras clave: Sentimiento, Productividad de los Empleados, Aprendizaje Automático, Pandemia.

INTRODUCTION

A pandemic seems to be a once-in-a-lifetime event that may have far-reaching repercussions on the global economy. The COVID-19 pandemic put nations across the globe under lockdown. Social distancing has become the new normal for humans to survive the deadly virus **(Shoesmith et al., 2021)**. Remote working arrangements flourished under this new normal. With the steady increase in jobs with remote working possible, more people are working from home [WFH] allowing them greater flexibility to manage work and family by reducing commute time, flexibility in work hours, higher work-life balance,etc. **(Gibbs et al., 2021)**.

Every coin has two sides and so does WFH, while it may offer some rewards to employees on the personalfront organizations feel there is a rift in the training and hiring process due to remote work **(WSJ, 2020)**. In this paper, we have assessed the sentiments of employees of a mid-sized consultancy firm and established its correlation with workplace productivity. The company had to switch to the WFH model dueto COVID-19 and has now incorporated the Hybrid working model as a part of its culture, giving employees the liberty to work from anywhere.

One of the primary concerns of organizations post-COVID-19 pandemic is improving employee productivity. The notion that organizational success is dependent on employee productivity is well established, thus it has become imperative for business **(Hanaysha, 2016)**. It can be onerous to measure productivity and compare the results due to the myriad of approaches followed **(Nollman, 2013)**. The time during which an employee is working efficiently or rather ‘mentally present’ at work can be the basis for measuring employee productivity **(Sharma, 2014)**.

Higher productivity results in higher success rates, enhanced work culture, competitive compensation,and greater profits **(Cato & Gordon, 2009)**. This culminates in motivating and inspiring the employeesto spark their creativity and achieve the pinnacle of their productivity **(Obdulio, 2014)**. COVID-19 pandemic has enforced WFH on numerous employees. Studies have shown a negative correlation between WFH and productivity **(Farooq & Sultana, 2021)**. Whereas it has been observed that, commuting distance is positively correlated to absenteeism in employees. The shorter the commute to the work, the higher is the productivity. Also, active mode of transport such as cycling or walking to work not only impacts employees’ health positively but also suggests better job performance **(Ma & Ye, 2019)**.

Various factors influence productivity, they can be environmental factors such as air, temperature, colour, light, space, and sound or organizational norms such as democratic leadership **(Almaamari & Alaswad, 2021; Singh, 2020)**. Age or rather employee experience can be a decisive factor in elevatingworkplace productivity **(Singh, 2020)**, also excellent stress management functions in the company canalleviate physical and psychological fears among the employees which directly improves organizationaleffectiveness by increasing productivity **(Sulaiman & Allah Baksh, 2019)**.

Money is the most crucial motivator when it comes to working. It can act as a stimulant and enhance employee productivity when combined with workplace discipline and motivation in form of appreciations and feedbacks **(Indah et al., 2020)**. People work better in a safe and hazard free environment which is created by company’s safety policy and employee job satisfaction. It is positively correlated to the employee productivity **(Morgan Morgan et al., 2021)**. With vast number of people opting for WFH, the office environment is missing from daily work. Workplace ergonomics have beenshown to be conducive to increasing employee productivity by creating an ergonomic environment which includes seating arrangements, type of chairs, use of glass etc **(Kumar et al., 2019)**.

The primary objective of the Human Resources function of any organization is to keep their employeessatisfied and happy (Harlianto, J., & Rudi. ,2023).To do so, policies must be designed which creates an environment of collaborationand generates productive outcomes **(Gaye et al., 2021)**. Technology adoption acts as a mediator for HR competency enhancement (Qaralleh, S. J., Rahim, N. F. A., & Richardson, C. (2023). Evidence-based relationships between objectives and Human Resources function can be established by utilizing predictive analytics tools. They utilize techniques such as Data Mining and application of various algorithms that can be used for sentiment analysis **(Malisetty et al., 2017)**. Sentiment analysis classifies the text data into positive, negative, andsometimes neutral sentiment based on the different machine learning algorithms used. Supervised and unsupervised learning can be used in order to predict the sentiment of the given text **(Medhat et al., 2014)**. For supervised learning methods, a pre labelled data set is used for analysis the unknown data which is a laborious task. Whereas unsupervised learning uses a pre-defined library for analysing the text data **(R. Khan, 2021)**.

With myriad of research being done on work engagement **(Hanaysha, 2016)**, employee behaviour monitoring **(Bawane et al., 2021)** and employee satisfaction and its effect on firm's earning **(Moniz & De Jong, 2014)** using sentiment analysis, the authors have attempted to correlate employee sentimentswith workplace productivity.

The objective of this study was to establish a correlation between employee sentiment and workplace productivity by comparing the sentiment score predicted by Valence Aware Dictionary and Sentiment Reasoning (VADER) method from the text input given by employees to their productivity score whichwas calculated based on their responses to the questions asked. A positive correlation i.e., a higher productivity score corresponding to a positive senti ment score, indicates that a positive sentiment amongthe workforce might be a contributing factor for enhanced workplace productivity.

From the literature review it was evident that productivity is not a function of a single factor. It varies with the magnitudes of the factors mentioned in the literature. The productivity score ranges from one to five with score above and equal to three are considered productive. Similarly, the sentiment score ranges from negative one to positive one with score above and equal to zero are considered positive sentiments. Studying sentiments as a function of productivity was novel and unexplored. Thus, the authors have proposed the following hypotheses for the study.

A. H_0 – Workplace productivity is not correlated to employee sentiments.

H_1 – Workplace productivity is correlated to the employee sentiments.

B. H_0 – Mean productivity score for the sample population = 3H_1 – Mean productivity score for the sample population > 3

C. H_0 – Mean sentiment score for the sample population = 0 H_1 – Mean productivity score for the sample population > 0

METHODOLOGY

The study entails a survey of seventy-two employees of a mid-sized consulting firm through a structuredquestionnaire. The survey consisted of three sections wherein the first section sought demographic information such as the age and sex of the respondents. The second section consisted of sixteen statements/ questions for assessing the productivity levels of the respondents, and the third section had three questions to which respondents had to type a text-based answer. These text answers were input for the sentiment analysis. A survey questionnaire was prepared using Google forms, whereas statistical analysis was performed on Microsoft Excel. Sentiment analysis computing was done using Jupyter notebooks **(Kluyver et al., 2016),** libraries used for analysis are Natural Language Toolkit **(Wagner, 2010),** pandas **(McKinney, 2010)**, NumPy **(Harris et al., 2020)**, SciKit Learn **(Pedregosa FABIANPEDREGOSA et al., 2011)**.

The survey was executed online via email over a span of two weeks. Respondents were implored to give their responses to the best of their experience and knowledge.

RESULTS AND DISCUSSION

VADER (Valence Aware Dictionary and Sentiment Reasoner) **(Hutto, C.J. and Gilbert, 2014)** is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media. VADER uses a combination of sentiment lexicon which is a list of lexical features (e.g., words) that are generally labeled according to their semantic orientation as either positive or negative. VADER not only talks about the Positivity and Negativity score but also tells us about how positive or negative a sentiment is **(Geeks for**

Geeks, 2022).

A negative score indicates a negative sentiment and vice-versa, zero can be assumed to be neutral or positive. In this study, three questions had text-based input which was inputs for the VADER sentimentanalyzer. An average of three sentiment scores was taken for individual respondents, which was assigned as the overall sentiment score.

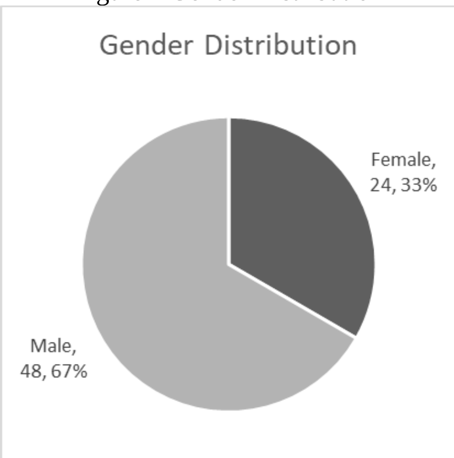
Productivity Score Analysis

Sixteen questions were posed to the respondents which they answered on a five-point Likert scale. The probable responses were *'Not at All', 'Rarely', 'Sometimes', 'Often', and 'Very Often'*. To calculateproductivity scores, these responses were assigned a numeric value based on the merit of the question from one to five. Five indicated that the respondent showed high productivity on a particular question item whereas one showed otherwise. Three was considered the midpoint for demarcation between productive and unproductive scores. Further, an average of sixteen such scores was taken and assigned as an overall productivity score.

All the hypothesis validation was performed on Microsoft Excel where $p < 0.05$ was a minimum level ofsignificance.

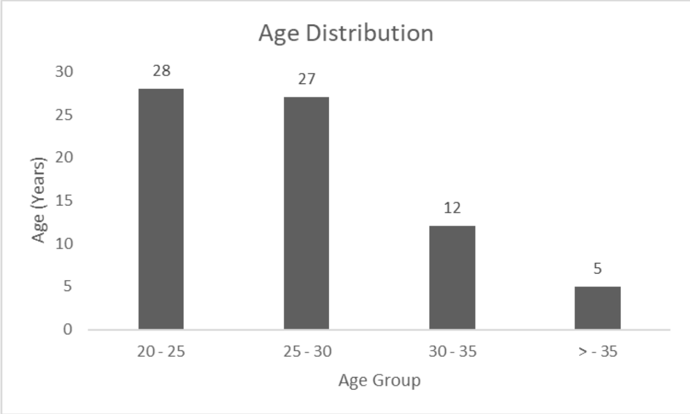
The demographic details of the population revealed a 1:2 ratio of females to male respondents with over76% of the population under the age of 30.

Figure 1 Gender Distribution



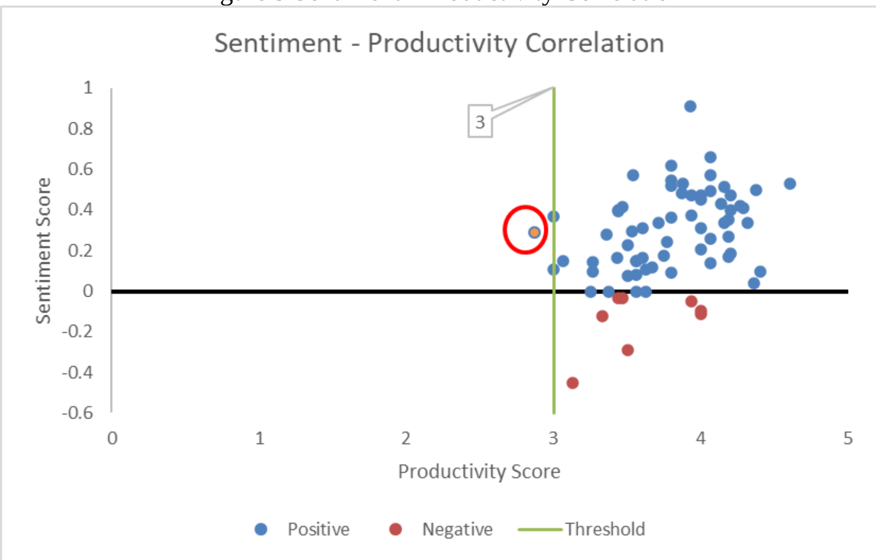
Source: Prepared by authors (2022)

Figure 2 Age Distribution



Source: Prepared by authors (2022)

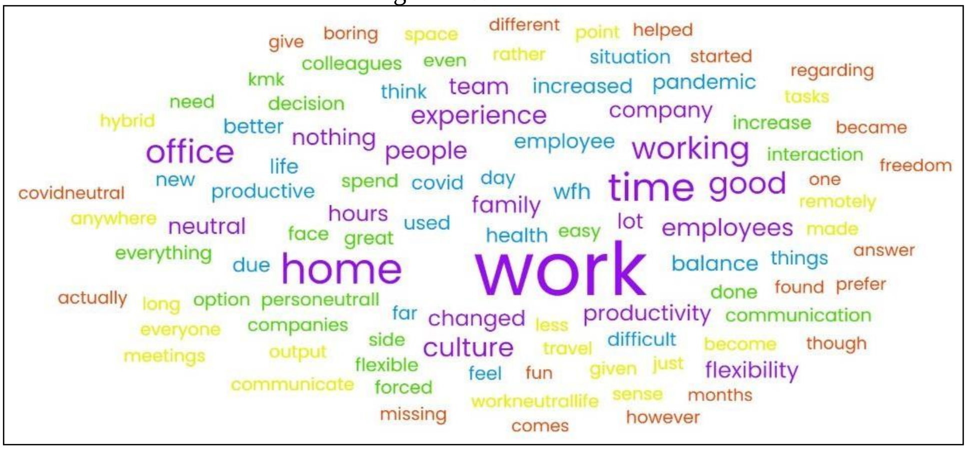
Figure 3 Sentiment - Productivity Correlation



Source: Prepared by Authors (2022)

71 of the 72 i.e., 98.6% respondents scored above or equal to 3 on the productivity score, whereas 64 i.e., 88.9% of them score above and equal to 0 on the sentiment score. The correlation between sentiment score and productivity score shows a positive relationship. The majority of the 8 negative sentiments in the high productivity zone can be considered as borderline negative or neutral sentiments. Only 1 respondent scored below 3 on the productivity scale but has a positive sentiment score, this can be considered as borderline productive.

Figure 4 Word Cloud



Source: Prepared by Authors(2022)

The above figure shows a word cloud of frequent terms used by respondents in their text responses. Thesize of the words indicates their frequency of use.

CONCLUSION

In conclusion it was found that the overall sentiment scores and overall productivity scores were positively correlated. Thus, we can safely posit that an employee with positive work sentiments is a productive employee. Because the respondents were working in a hybrid work model and scored high on both the sentiment and productivity metrics, we can say that workplace is not restricted to only offices, but it entails all the places where an employee can possibly work.

The machine learning model used for this study is not capable of detecting sarcasm. Thus, any responsewhich may have been sarcastic in nature would be classified falsely. Some of the respondents did not fill the text-based answers appropriately, they were removed from the analysis to reduce errors. The research was carried out focusing a single firm, more comprehensive research of large firms would have added to the quality of the outcome.

The current study aims at understanding the relationship between productivity and employee sentiments; however, emphasis could be put on understanding the underlying factors for productivity and sentiments along with their contributions to respective terms by conducting a factor analysis. The role of gender and age can also be studied as they can be contributing factors as well.

REFERENCES

Almaamari, Q. A., & Alaswad, H. I. (2021). FACTORS INFLUENCING EMPLOYEES'

PRODUCTIVITY- LITERATURE REVIEW. *Academy of Entrepreneurship Journal*, *27*(3), 1–7.

Bawane, D., Bhojane, R., & Ganage, A. (2021). Employee behavior monitoring and sentiment analysis prediction using machine learning. *International Research Journal of Engineering andTechnology (IRJET)*, *8*(3), 1379–1383.

Farooq, R., & Sultana, A. (2021). The potential impact of the COVID-19 pandemic on work from home and employee productivity. *Measuring Business Excellence*. https://doi.org/10.1108/MBE-12-2020-0173

Gaye, B., Zhang, D., & Wulamu, A. (2021). Sentiment classification for employees reviews using regression vectorstochastic gradient descent classifier (RV-SGDC). *PeerJ Computer Science*, *7*,1–27. https://doi.org/10.7717/peerj-cs.712

Gibbs, M., Mengel, F., & Siemroth, C. (2021). Work from Home & Productivity: Evidence fromPersonnel & Analytics Data on it Professionals. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3846680

Hanaysha, J. (2016). Improving employee productivity through work engagement: Evidence fromhigher education sector. *Management Science Letters*, *January*, 61–70. https://doi.org/10.5267/j.msl.2015.11.006

Harris, C. R., Millman, K. J., van der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., Wieser,E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., van Kerkwijk, M. H., Brett, M., Haldane, A., del Río, J. F., Wiebe, M., Peterson, P., … Oliphant, T. E. (2020). Array programming with NumPy. In *Nature* (Vol. 585, Issue 7825). https://doi.org/10.1038/s41586- 020-2649-2

Hutto, C.J. and Gilbert, E. (2014). VADER: A Parsimonious Rule-based Model for. *Eighth International AAAI Conference on Weblogs and Social Media*, 18. https://www.aaai.org/ocs/index.php/ICWSM/ICWSM14/paper/viewPaper/8109

Indah, G., Sukarta, P., Sagung, A. A., & Dewi, K. (2020). Effect of Work Compensation, Motivationand Discipline on Employee Productivity. *American Journal of Humanities and Social SciencesResearch*, *4*(2), 27–33. www.ajhssr.com

Kluyver, T., Ragan-Kelley, B., Pérez, F., Granger, B., Bussonnier, M., Frederic, J., Kelley, K.,

Hamrick, J., Grout, J., Corlay, S., Ivanov, P., Avila, D., Abdalla, S., & Willing, C. (2016). Jupyter Notebooks—a publishing format for reproducible computational workflows. *Positioningand Power in Academic Publishing: Players, Agents and Agendas - Proceedings of the 20th International Conference on Electronic Publishing, ELPUB 2016*. https://doi.org/10.3233/978- 1-61499-649-1-87

Kumar, G. R., Bezawada, S. T., Sinno, N., & Ammoun, M. (2019). The impact of ergonomics on employees' productivity in the architectural workplaces. *International*

Journal of Engineering and Advanced Technology, *8*(5), 1122–1132. https://doi.org/10.35940/ijeat.E1157.0585C19

Ma, L., & Ye, R. (2019). Does daily commuting behavior matter to employee productivity? *Journal ofTransport Geography*, *76*, 130–141. https://doi.org/10.1016/j.jtrangeo.2019.03.008

Malisetty, S., Archana, R. V., & Vasanthi Kumari, K. (2017). Predictive analytics in HR Management. *Indian Journal of Public Health Research and Development*, *8*(3), 115–120.https://doi.org/10.5958/0976-5506.2017.00171.1

McKinney, W. (2010). Data Structures for Statistical Computing in Python. *Proceedings of the 9thPython in Science Conference*. https://doi.org/10.25080/majora-92bf1922-00a

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications : A survey. *Ain Shams Engineering Journal*, *5*(4), 1093–1113. https://doi.org/10.1016/j.asej.2014.04.011

Moniz, A., & De Jong, F. (2014). Sentiment analysis and the impact of employee satisfaction on firmearnings. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *8416 LNCS*, 519–527. https://doi.org/10.1007/978-3-319-06028-6_51

Morgan Morgan, O., Emu, W., Amadi, C., Okon, E., & Njama, P. (2021). The mediating effect of jobsatisfaction on health and safety policy management and employee productivity in manufacturing firms. In *Problems and Perspectives in Management* (Vol. 19, Issue 2, pp. 104– 117). LLC CPC Business Perspectives. https://doi.org/10.21511/ppm.19(2).2021.09

Nollman, M. R. (2013). *Sustainability Initiatives in the Workplace and Employee Productivity*. Pedregosa FABIANPEDREGOSA, F., Michel, V., Grisel OLIVIERGRISEL, O., Blondel, M.,

Prettenhofer, P., Weiss, R., Vanderplas, J., Cournapeau, D., Pedregosa, F., Varoquaux, G., Gramfort, A., Thirion, B., Grisel, O., Dubourg, V., Passos, A., Brucher, M., Perrot andÉdouardand, M., Duchesnay, andÉdouard, & Duchesnay EDOUARDDUCHESNAY, Fré. (2011). Scikit-learn: Machine Learning in Python Gaël Varoquaux Bertrand Thirion Vincent Dubourg Alexandre Passos PEDREGOSA, VAROQUAUX, GRAMFORT ET AL. Matthieu Perrot. In *Journal of Machine Learning Research* (Vol. 12). http://scikit-learn.sourceforge.net.

Shoesmith, E., Shahab, L., Kale, D., Mills, D. S., Reeve, C., Toner, P., de Assis, L. S., & Ratschen, E.(2021). The influence of human–animal interactions on mental and physical health during the first COVID-19 lockdown phase in the U.K.: A qualitative exploration. *International Journal of Environmental Research and Public Health*, *18*(3), 1–15. https://doi.org/10.3390/ijerph18030976

Singh, A. (2020). Association between organizational norms and employee productivity in highereducation. *Journal of Applied Research in Higher Education*, *12*(2), 271–295. https://doi.org/10.1108/JARHE-01-2019-0014

Sulaiman, N., & Allah Baksh, S. (2019). Role of stress management in increasing employee productivity at workplace. *International Journal of Recent Technology and Engineering*, *8*(2 Special Issue 4), 744–746.

https://doi.org/10.35940/ijrte.B1150.0782S419

Wagner, W. (2010). Steven Bird, Ewan Klein and Edward Loper: Natural Language Processing with Python, Analyzing Text with the Natural Language Toolkit. *Language Resources and Evaluation*, *44*(4). https://doi.org/10.1007/s10579-010-9124-x

Obdulio, D. L. (2014). How management can improve corporate culture in order to have an effectivework environment. Trade Publication, 75(8), 14.

R. Khan, F. Rustam, K. Kanwal, A. Mehmood and G. S. Choi, "US Based COVID-19 Tweets Sentiment Analysis Using TextBlob and Supervised Machine Learning Algorithms," 2021International Conference on Artificial Intelligence (ICAI), 2021, pp. 1-8, doi: 10.1109/ICAI52203.2021.9445207.

Sharma, M. S., & Sharma, M. V. (2014). Employee engagement to enhance productivity in currentscenario. International Journal of Commerce, Business and Management, 3(4), 595-604.

WSJ (2020): “Companies Start to Think Remote Work Isn’t So Great After All,” https://www.wsj.com/articles/ companies-start-to-think-remote-work-isnt-so-great-after-all-11595603397.

Qaralleh, S. J., Rahim, N. F. A., & Richardson, C. (2023). JOB RESOURCE AND JOB PERFORMANCE AMONG PHYSICIANS IN THE JORDANIAN HEALTH SECTOR: THE MEDIATING ROLE OF JOB SATISFACTION. [RECURSOS DE EMPREGO E DESEMPENHO NO TRABALHO ENTRE MÉDICOS NO SETOR DE SAÚDE DA JORDÂNIA: O PAPEL MEDIADOR DA SATISFAÇÃO NO TRABALHO; RECURSOS LABORALES Y RENDIMIENTO LABORAL DE LOS MÉDICOS DEL SECTOR SANITARIO JORDANO: EL PAPEL MEDIADOR DE LA SATISFACCIÓN LABORAL] *International Journal of Professional Business Review*, *8*(1) doi:10.26668/businessreview/2023.v8i1.378

Harlianto, J., & Rudi. (2023). Promote Employee Experience for Higher Employee Performance. *International Journal of Professional Business Review*, *8*(3), e0827. https://doi.org/10.26668/businessreview/2023.v8i3.827