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IMPACT OF WORKFORCE EMOTIONAL INTELLIGENCE ON PATIENT SATISFACTION: A SENTIMENT ANALYSIS APPROACH USING SUPERVISED MACHINE ALGORITHMS

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ABSTRACT

In the present competitive scenario emotional intelligence has gained paramount consideration, especially in Job roles with inherent stress. In the health care sector, patient satisfaction is the major area of concern and emotional intelligence of work force may trigger to patient satisfaction. The three important attributes of emotional intelligence related to inter personal skills are identified as Social Skills, Empathy and Intrinsic Motivation. Text reviews were collected from 884 patients admitted in private ward in hospitals to measure the association amongst emotional intelligence of workforce and patient satisfaction. The three dimensions of emotional intelligence are classified with the help of lexicon-based approach. Sentiment from textblob, Afinn and VADER are used for determination of the sentiments of the three dimensions of emotional intelligence. Before developing the models all the assumptions of regression analysis are tested. The models were developed with the help of six diverse supervised machine learning algorithms. Best expected outcome was achieved by the gradient boosting model. All the three dimensions were found to be significant contributors to the patient satisfaction level. However, the highest contribution was from 'Empathy', followed by 'Social Skills' and least was found to be for 'Intrinsic Motivation'. Since emotional intelligence is not a constant attribute, training can be imparted to improve emotional control of staff. This will help in enhancing patient care by observing behavioral patterns.

Keywords: Emotional Intelligence, patient Satisfaction, social skills, empathy, intrinsic motivation, sentiment analysis.

I. INTRODUCTION

Emotions have an important impact on personal and professional lives and they are considered as troublesome particularly in professional world. If emotions are not controlled and concealed, they would hamper the functioning of the organization. Dalip (2006) expressed the importance of emotional sensitivity, maturity and competency. Managing emotions is more important in professions which requires interaction with people like healthcare industry requires to deal with patients, service industry needs to communicate with customers etc. Emotional intelligence is the capability to recognize, read, use, comprehend and regulate emotions for enhanced communication and effective results. It helps to generate an awareness and sensitivity towards others emotions and plays an important role in managing stress and conflict resulting to better job performance. In health care industry, anxiety of patient may rise from physical, emotional and financial issues and professionals may really find it difficult to handle daily situations. Researchers (Brewer and Cadman, 2001; Epstein and Hundert, 2002; Freshwater, 2004; Herbert and Edgar, 2004) suggest that emotional intelligence is necessary for imparting patient centered care. Assessing patient's emotional reactions to prescribed treatments or lifestyle can help to identify problems and difficulties, clarify doubts and increase empathy. This will result to a less stressful environment and boost the relationship between the professional and patient through better understanding and enhanced patient care. Increased emotional intelligence can thus strengthen the quality leading to better productivity and hence be considered as a distinguishing factor in the health care industry.

Reviews help the organization to derive meaningful and valuable insights. Attitudes, sentiments and views can be examined with the help of sentiment analysis. The majority of studies have used social media data for sentiment analysis. Facebook, Twitter, Instagram etc. are different social media channels that cover substantial text data about a product or service from various online users. Sentiment analysis can assess this information available from different social media channels for understanding the emotions involved. As a result of posts from users who might have uploaded the information without their knowledge, reviews made by users on social media may not give a fair image of the situation. In order to accurately represent the patient's perspective on the emotional intelligence of the work force, in our study we have compiled reviews from patients who have experienced the hospital work force.

Some of the researchers (Giardini and Frese, 2006; Birks and Wattz, 2007; Ashkanasy and Daus, 2005) have expressed that emotional intelligence has emerged as an important factor, but there is dearth of good studies in the health care sector. It has become imperative for the organizations to realize importance of data and analytics in healthcare sector for organizational decisions. It is important to unlock the true value of workforce and determine the relationship between score of patient satisfaction and emotional intelligence.

II. LITERATURE REVIEW

Cooper and Sawaf, (1998) state that the capability to comprehend and effectually apply the acumen of sentiments as a cause of energy, belief, ingenuity and impact is emotional intelligence. Shanwal (2004) states that emotional intelligence is "the awareness of use of emotions and their utilization within the parameters of individual cognitive styles to cope with situations and problems". "Emotional intelligence is defined as the ability to adaptively perceive, understand and regulate emotions in oneself and others person" (Salovey and Mayer, 1990; Schutte et al.,1998). "Emotional Intelligence is habitual practice of using and regulating emotional information from ourselves and other people, integrating this with our thinking and using these to inform our decision making to help us get what we want" (Sparrow and Knight, 2006, Bar-On, 2000).

Bar-On (1977), Daniel Goleman (1995) and Mayer and Salovey (2004) were the initial researchers to delve in to emotional intelligence. According to Bar-On (1977), ability to comprehend oneself and others in order to succeed in accordance with environmental expectations is emotional intelligence. Mayer and Salovi (2004) expressed that it involves cognition, evaluation and expression of emotions. However, Goleman (1995) self-awareness, motivation, self-regulation, empathy, motivation and social skills are the five dimensions of emotional intelligence. Self-regulation and awareness helps to understand our own strength and weaknesses and manage our emotions specifically in complex situations. Effective communication and better organizational environment can be achieved through developing an understanding of others emotions. Emotionally intelligent people are generally motivated and are passionate about their job. Griffin and Moorhead (2007) state that emotional competence (achievement, commitment, initiative, optimism etc.) is a characteristic of highly motivated people. Empathy is associated with keeping ourselves in someone else's shoes, which helps in understand their feeling and reaction in specific circumstances.

Stressful and complex conditions are effectively managed by people with a higher level of emotional intelligence. They are more aware and sensitive towards other's feelings, listen, empathize and effectively manage disturbing emotions. Hospitals can be a stressful place and various stressful conditions may exist when the workforce might need to deal with own and patient emotions. The healthcare providers have long working hours and has excessive workloads including complicated tasks like managing patient complaints, interference from families, sharing the difficult news with patients and their families, avoiding serious mistakes etc. This can lead to burnout and increased stress levels of the workforce, insufficient patient care, clinical mistakes and finally lead to dissatisfaction amongst patients. In order to meet societal needs in the hospital, it becomes crucial to have clinical expert and emotionally intelligent workforce. This will help in effective understanding of the patient problems, maintaining better relations, thereby providing them easy and comfortable recovery resulting to increased productivity, patient positive attitude and better output of hospitals.

A person's emotional intelligence can be said to be equivalent to his intellectual and technical talent. (Arora, 2017), It helps in improving self-management, and its effects are perceived through relationship management or sympathy. (Goleman, 2004) and positively connected with organizational commitment (Matheri, 2020, Naz et al., 2019). Emotional intelligence was identified to be a significant predictor for making better inter personal relations positive work attitude, job performance and employee satisfaction (Carmeli and Josman, 2006; Kim et al., 2009;

Gunavathy and Ayswarya, 2011; Wong, 2004, Tram and O'Hara, 2006; Njoroge and Yazdanifard, 2014). Nanda and Randhawa (2020) shows that emotional intelligence has direct relationship with its measurements such as work engagement, job satisfaction and job stress. Brooks (2003) states that managers with higher performance rating possess high emotional intelligence as compared to managers with lower rating.

Some researchers have done study using emotional intelligence in health care sector related to different domains. Sovie and Jawad (2001) state a significant relation between patient satisfaction and delivery of patient care. Wagner et al. (2002) in their study on 30 doctors and 138 patients in USA conclude that there is no significant relationship between satisfaction and emotional intelligence. Gerits et al. (2005) did a study on 380 nurses in Netherlands who are dealing with people having mental retardation and complex behavioural problems. They created groups based on different emotional intelligence and genders. In female nurses low scores were associated with higher burnout; while emotional intelligence scores were related to personal achievement for males. Humpel, Caputi and Martin (2008) in their study on nurses in Australia found, lower emotional intelligence scores in female nurses.

Sentiment analysis is a methodology that makes use of natural language processing techniques for interpreting opinion from a text and classifying it into different categories of sentiment. Sentiment analysis can be done by using either supervised machine learning approach or lexicon-based approach (Unsupervised machine learning). In supervised learning, sentiment analysis starts with label texts and trains on the label text data to detect sentiment and the polarity of new texts. Since the Lexicon Method does not require training of data, it is used and the results are entirely dependent on the scores given to the words and phrases. Sentiment analysis has been utilized in a variety of business settings, most notably in marketing and finance, there is a need for determining its application in the healthcare industry. Researchers (Mantyla et al., 2018; Druz and Khalid, 2019) has done an extensive literature review related to sentiment analysis research. Rambocase and Pacheco (2018) in their study state that majority of the articles analysed text mined from social media particularly from Twitter and sentiment analysis was done for opinions related to different events, politics and business (Druz and Khalid, 2019). Sentiment analysis on customer feedback can assist organizations to improve their product or services by better formulation of effective business strategies (Akter et al., 2016; Gursoy et al., 2017; Poecze, Clause and Christine, 2018; Ikoro et al. 2018; Rahman et al., 2019).

For sentiment analysis many researchers (Hao and Hongying,2016; Akter et al., 2016; Shayaa et al., 2017; Karamollaoğlu et al. 2018, Ikoro et al., 2018; Mansour,2018) have used lexicon based approach. Researchers like (Ali et al., 2017; Hassan et al.,2017; Martin-Domingo et al., 2019) have performed sentiment analysis using a machine learning approach. In order to increase the model's accuracy, Dhaoui et al. (2017), Hassan et al. (2017), and Isah, Trundle, and Neagu. (2014) combined two strategies for sentiment analysis. Al-Shabi (2020) in his study compared the performance of various lexicons including VADER, Liu and Hu opinion lexicon, and AFINN-111, He concluded that Vader had the highest classification accuracy. According to Ragini et al. (2018), the lexicon method is the most effective way to comprehend customer feedback.

III. RESEARCH METHODOLOGY

The study makes use of Goleman's three elements namely social skills, empathy, and intrinsic motivation were taken into account while assessing the emotional intelligence of the hospital workers as assessment of self-regulation and self- awareness would be challenging. In order to ascertain the sentiment from the patient's viewpoint connected to three different aspects, resources like Afinn, VADER, and sentiment from textblob were taken into consideration. Information was collected from 884 hospitalised individuals. Due to incomplete responses to some questions, 1.1% of unreliable respondents were reported as per the findings of reliability control report. Final data from 802 patients were collected for the study.

Sentiment polarity refers to a score based on social and empathy skills that is related to both the positive and negative aspects of a text composition. It is challenging to assess oneself. There are no feelings or emotions; the thresholds can always be altered depending on the type of material. Polarity will be greater than zero for positive sentiment and less than zero for negative sentiment. rigid guidelines (Motwani,2020). Different lexicons were used for the sentiment analysis, the correctness of the lexicons' was assessed by manually dividing each review into good and negative category

The precision of sentiment analysis utilising Textblob, VADER and Afinn for the 'Social Skills' dimension was determined to be 0.848, 0.827, and 0.843, respectively. For dimension of 'Empathy', it was determined to be 0.8080, 0.6796, and 0.6521, respectively. For "Intrinsic Motivation" was 0.7768, 0.7955, and 0.7805. The thorough evaluation of the various lexicons reveals Textblob to be an ideal lexicon for our dataset. (Annexure A). Therefore, the regression model was created with the help of the results of textblob for assessing the influence of emotional intelligence on patient satisfaction. Before creating the model, the various regression analysis assumptions were examined using several supervised learning techniques.

Assumptions check before applying regression analysis:

The results of the outlier test show that there was no residual for p 0.5, thus we can conclude about the data being normal,

After running the outlier test, it was determined that there was no residual for p = 0.5, allowing us to conclude that the data is normal. Furthest away from the queue was 172. Using the Shapiro-Wilk test, W = 0.99 and p is 0.06 (>0.05). The presumption of normality was so confirmed. 'Social Skills', 'Empathy', and 'Intrinsic Motivation' were found to have correlations of 0.363, 0.352, and 0.259 with the dependent variable, 'patient satisfaction,' respectively. Since there is a correlation between the dependent variable and every independent variable, even if it is very low, the linearity requirement is met. Using the Durbin Watson Test, the independence of mistakes assumption was tested, and the value was discovered to be 1.79,hence independence of errors assumption is met. The Breusch-Pagan test and the ncv Test() function are used to implement the homoscedasticity assumption. This assumption was also met by the insignificant result of p (0.9383) >0.05. By calculating the variance inflation factor with the vif() function, the multicollinearity assumption was verified. This condition is met, the function sqrt (vif(model)) > 2 is false for each of the three independent variables.

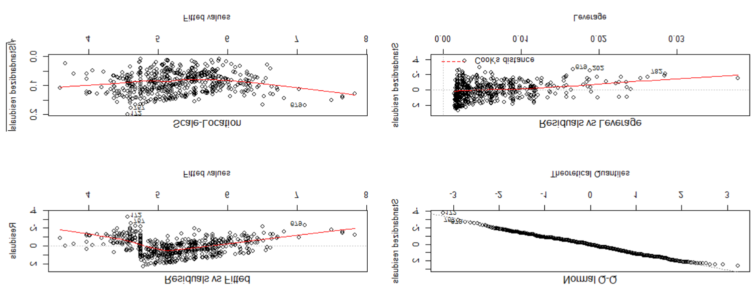

Fig 1: Normality Assumption before Applying Regression Analysis

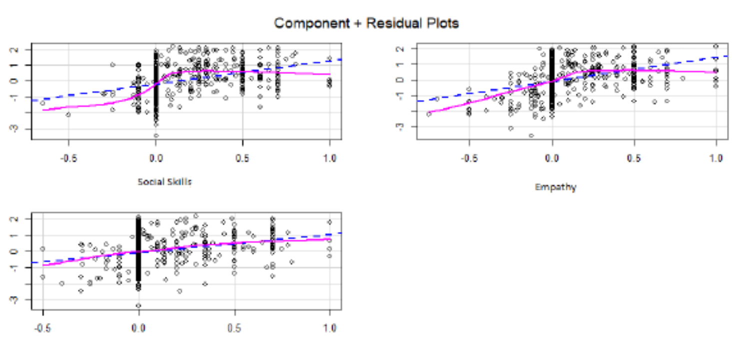

Fig 2: Component and Residual Plot for Independent Variables

The result of the graphical analysis of the assumptions is shown in figure 1 and 2. Almost all the points in Normal Q-Q plot falls on a straight, hence normality assumption is fulfilled (refer fig.1). The residuals and fitted plot show that there is no systematic relationship, hence the assumption of normality is also fulfilled (Fig 1 - Top Left). A proper band made around a horizontal line in scale location plot confirms the assumption of homoscedasticity (Fig 1 Bottom Left). It is clear from the fig 1 residual vs leverage chart that there is no specific outlier in our data. Fig 2 plots all component and residuals for independent variables- 'Social Skills', 'Empathy' and 'Intrinsic Motivation', which also show that assumption are fulfilled. Since, the graphical evaluation also shows that all the assumptions are fulfilled, hence we can now apply regression analysis on the data.

For building and testing the model, various supervised machine learning methods such as Linear Regression, KNN, and Support Vector Machines were used. The training and test datasets for Random Forest, Bagging, and Gradient Boosting were created. The training dataset was used to create the model, and the test dataset was used to evaluate it. It should be noted that hyper parameter tuning was performed for all algorithms to increase accuracy, and the optimal parameter values were found using a grid-based approach.

The parametrs such as 'max_features': 1.0, 'max_samples': 0.8, 'n_estimators': 20 in Bagging Model were found to best. The results of all of these algorithms are listed in Annexure B. The Gradient Boosting model has clearly produced the best expected results for the dataset used in the study, as evidenced by the results, where the RMSE value is the lowest. Due to limitations of NLP, all the models display a low accuracy. However, the accuracy can be increased by increasing the sample size.

Linear Regression Model equation:

Patient satisfaction = 4.79 + 1.47* 'Social Skills' + 1.50*'Empathy' +1.08*'Intrinsic Motivation'

The significance of predictor factors was found with the help of a decision tree model. "Empathy" (0.378) showed highest contribution followed by 'Social Skills' (0.35) and 'Intrinsic Motivation' (0.267) (Fig 3).

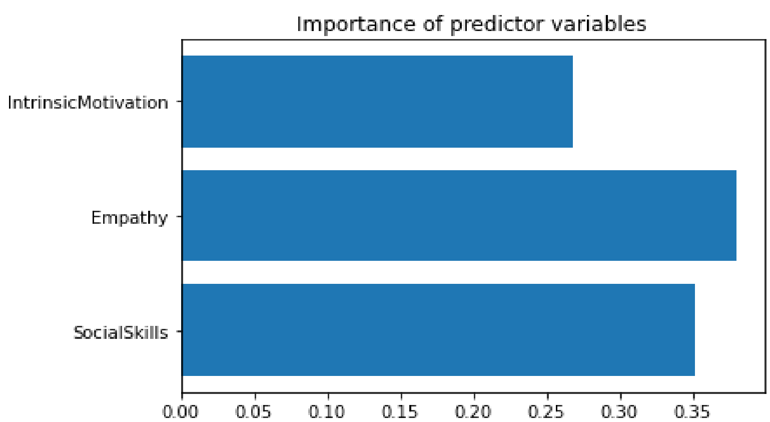

Fig 3: Importance of Predictor Variables

IV. CONCLUSION AND SUGGESTIONS

Emotional intelligence is an important skill that needs to be possessed by healthcare professionals for delivering improved quality of care and enhanced patient satisfaction. Intelligence is not restricted to the knowledge, but it also encompasses the ability to identify and recognize own and others emotions. Success of heath care sector depends on its work force which is accelerated through their emotional intelligence. In a competitive environment, workforce that drive clinical excellence along with emotional intelligence will determine the success of the hospital by maintain positive emotions in stressful and challenging circumstances. The emotionally intelligent workforce will be able to understand the different behavior of the patients in different circumstances, motivate themselves to manage all the situations, provide better health care experience for patients and their families and contribute to patient satisfaction. This study provides insight into the perceptions related to emotional intelligence of hospital staff and helps to understand the reasons of some heath care professionals gaining more success in achieving patient-centered care. The results of the study confirm that emotional intelligence drive into patient satisfaction and hence it is important for the health professionals to also meet the emotional needs of patients by observing certain behavioral patterns in their patients. The hospitals should hire emotionally matured people and take efforts for increasing the emotional intelligence level among the existing employees. Emotional intelligence is not a constant attribute and hence professionals who do not have a high level of emotional intelligence can always learn to improve control with proper training. Hospitals should extend assistance for promoting emotional intelligence by organizing emotional intelligence assessment and training on a regular basis. This will help the employees to increase their emotional self-awareness, resourcefulness, acceptance, confidence and reliability resulting to better interactions and more harmonious relationship.

V. LIMITATIONS

Before the importance of emotional intelligence can be properly proven, more research is necessary. The model was trained using three ensemble strategies under the supervision of machine learning. The models' accuracy, however, was not found to be very good. It is necessary to make efforts to increase accuracy, for as by developing a lexicon specifically for the health care sector. It is possible to conduct additional research to develop a feature engineering technique for creating improved performance.

Only three aspects of emotional intelligence were taken into account in this study to determine its effect on patient satisfaction. Before the importance of emotional intelligence can be properly proven, more research is necessary. The model was trained using three ensemble strategies under the supervision of machine learning. The models' accuracy, however, was not found to be very good. It is necessary to make efforts to increase accuracy, for as by developing a lexicon specifically for the health care sector. It is possible to conduct additional research to develop a feature engineering technique for creating improved performance. The accuracy of translation-based sentiment analysis methodologies increased from 72.2% to 80.4% (Saglam et al.,2019) creation of a better lexicon. Since, our classifier differentiated only between the positive and negative sentiments, we were not able to distinguish the rate of a positive or negative statement. They were categorized as extreme positive and negative. Future work on five sentiment classes strongly positive, mildly positive, neutral, mildly negative, and strongly negative can be done for analysts and practitioners.

REFERENCES

Akter, S., Tareq, M. A. (2016). Sentiment Analysis on Facebook Group Using Lexicon Based Approach.3rd International Conference on Electrical Engineering and Information Communication Technology.

Ali, K., Hai D., Bouguettaya, A., Erradi, A., Hadjidj, R. (2017). Sentiment Analysis as a Service: A Social Media Based Sentiment Analysis Framework. IEEE International Conference on Web Services.

Al-Shabi, M.A. (2020). Evaluating the Performance of the most Important Lexicons used to Sentiment Analysis and Opinions Mining. *International Journal of Computer Science and Network Security,* 20(1).

Arora, B. (2017). Importance of Emotional Intelligence in the Workplace. *International Journal of Engineering and Applied Sciences,* 4(4).

Ashkanasy, N., Daus, C. (2005). Rumors of Death of Emotional Intelligence in Organizational Behavior are Vastly Exaggerated. *Journal of Organizational Behavior*, 26(4), 441-452.

Awwad, H., Alpkocak, A. (2016). Performance Comparison of Different Lexicons for Sentiment Analysis in Arabic. Third European Network Intelligence Conference, Wroclaw, 127-133.

Birks,Y., Wattz, I.Z. (2007). Emotional Intelligence and Patient-Centered Care. *Journal of the Royal Society of Medicine*, 100, 368–374.

Bar-On, R. (1997). *Bar-One Emotional Quotient Inventory: Technical Manual*. Toronto: Multi-Health Systems.

Bar-On, R. (2000). *Emotional and Social Intelligence: Insights from the Emotional Quotient Inventory*. In Bar-On, R. and Parker, J., Handbook of Emotional Intelligence. Jossey-Bass.

Brooks, J. K. (2003). Emotional Competencies of Leaders: A Comparison of Managers in a Financial Organization by Performance Level.

Cadman, C., Brewer, J. (2001). Emotional Intelligence: A Vital Prerequisite for Recruitment in Nursing. *Journal of Nursing Management*, 321–4.

Carmeli, A., Josman, Z. E. (2006). The Relationship among Emotional Intelligence, Task Performance, and Organizational Citizenship Behaviors. *Human Performance*, 19(4), 403–419.

Cooper, R. K., Sawaf, A. (1998). *Executive EQ: Emotional Intelligence in Leadership and Organizations.* Penguin.

Dalip, S. (2006). *Emotional Intelligence at Work, A Professional Guide.*

Dhaoui, C., Cynthia, M., Peng, T. (2017). Social Media Sentiment Analysis: Lexicon versus Machine Learning. *Journal of Consumer Marketing,* 34 (6), 480-488.

Drus, Z., Khalid, H. (2019). Sentiment Analysis in Social Media and its Application: Systematic Literature Review. The Fifth Information Systems International Conference, Procedia Computer Science 161, 707–714.

Epstein, R.M., Hundert, E.M. (2002). Defining and Assessing Professional Competence. *Journal of the American Medical Association*, 226–35.

Freshwater, D., Stickley, T. (2004). The Heart of the Art: Emotional Intelligence in Nurse Education. *Journal of Psychiatrics Mental Health Nursing*, 505–7.

Gerits, L., Derksen, J., Verbruggen, A.B., Katzko, M. (2005). Emotional Intelligence Profiles of Nurses Caring for People with Severe Behaviour Problems. *Personality and Individual Differences,* 38(1), 33-43.

Giardini, A., Frese, M. (2006). Reducing the Negative Effects of Emotion Work in Service Occupations: Emotional Competence as a Psychological Resource. *Journal of Occupational Health Psychology*, 11(1), 63-75.

Goleman, D. (2004). What makes a Leader? *Harvard Business Review*, 82, 82-91.

Griffin, R., Moorhead, G. (2007) *Organizational Behavior: Managing People and Organizations.* Houghton Mifflin Company.

Gunavathy J., Ayswarya R. (2011), Emotional Intelligence and Job Satisfaction as Correlation of Job Performance – A Study among Women Employed on Indian Software Industry.

Gursoy, U.T., Bulut, D, Yigit, C. (2017). Social Media Mining and Sentiment Analysis for Brand Management. *Global Journal of Emerging Trends in e-Business, Marketing and Consumer Psychology*, 3 (1), 497-551.

Hao, J. & Hongying, D. (2016). Social Media Content and Sentiment Analysis on Consumer Security Breaches. *Journal of Financial Crime*, 23 (4), 855-869.

Hassan, Anees U., Jamil H., Musarrat H., Muhammad, S. & Sungyoung, L. (2017). Sentiment Analysis of Social Networking Sites (SNS) Data Using Machine Learning Approach for the Measurement of Depression. International Conference on Information and Communication Technology Convergence.

Herbert, R. & Edgar, L. (2004). Emotional intelligence: a primal dimension of nursing leadership? *Journal of Nursing Leader,* 56–63.

Humpel, N., Caputi, P. & Martin, C. (2008). The Relationship between Emotions and Stress among Mental Health Nurses. *International Journal of Mental Health Nursing*.

Ikoro, V. Sharmina,M., Malik,K. & Batista-Navarro., R. (2018). Analyzing Sentiments Expressed on Twitter by UK Energy Company Consumers. Fifth International Conference on Social Networks Analysis, Management and Security, 95- 98.

Isah, H., Trundle, P. & Neagu, D. (2014). Social Media Analysis for Product Safety Using Text Mining and Sentiment Analysis. UK Workshop on Computational Intelligence.

Jeong, B.K., Yoon, J. & Lee, J.M.(2019). Social Media Mining for Product Planning: A Product Opportunity Mining Approach based on Topic Modeling and Sentiment Analysis. *International Journal of Information Management*, 48, 280-290.

Joyce, B. & Deng, J. (2017). Sentiment Analysis of Tweets for the 2016 US Presidential Election. MIT Undergraduate Research Technology Conference.

Karamollaoğlu, H., Doğru, I.A., Dörterler, M., Utku, A. & Yıldız, O. (2018). Sentiment Analysis on Turkish Social Media Shares through Lexicon Based Approach. International Conference on Computer Science and Engineering.

Khoo, C.S.G & Johnkhan, S.B. (2016). Lexicon-Based Sentiment Analysis: Comparative Evaluation of Six Sentiment Lexicons. *Journal of Information Science.*

Kim, T. Y., Cable, D. M., Kim, S. P. & Wang, J. (2009) Emotional Competence and Work Performance: The Mediating Effect of Proactivity and the Moderating Effect of Job Autonomy. *Journal of Organizational Behavior*, 30(7), 983-1000.

Lipizzi, C., Iandoli, L. & Marquez, J. (2015). Extracting and Evaluating Conversational Patterns in Social Media: A Socio-Semantic Analysis of Customers' Reactions to the Launch of New Products using Twitter Streams. *International Journal of Information Management*, 35(4), 490-503.

Mansour, S. (2018). Social Media Analysis of User's Responses to Terrorism using Sentiment Analysis and Text Mining. *Procedia Computer Science*, 140, 95–103.

Mäntylä, M. V., Graziotin & Kuutila, M. (2018). The Evolution of Sentiment Analysis—A Review of Research Topics, Venues, and Top Cited Papers. *Computer Science Review,* 27, 16-32.

Martin-Domingo, L., Martin, J.C. & Glen, M. (2019) Social Media as a Resource for Sentiment Analysis of Airport Service Quality. *Journal of Air Transport Management.*

Martinez-Pons, M. (1997). The Relation of Emotional Intelligence with Selected Areas of Personal Functioning. *Imagination, Cognition and Personality*, 17(1), 3–13.

Matheri, S. M. (2020). Effect of Emotional Intelligence on Employee Commitment in Savings and Credit Co-Operative Societies in Kenya.

Mayer, J.D., Salovey, P. (1993). The Intelligence of Emotional Intelligence. *Intelligence,* 17, 433-442.

Mayer, J. D., Salovey, P. & Caruso, D. R. (2004). Emotional Intelligence: Theory, Findings, and Implications. *Psychological Inquiry,* 15(3), 197–215.

Mayer, J. D., Salovey, P. & Caruso, D. R. (2008) Emotional Intelligence: New Ability or Eclectic Traits?. *American Psychologist*, 63(6), 503.

Mirtalaie, M.A. & Hussain, O.K. (2020). Sentiment Aggregation of Targeted Features by Capturing their Dependencies: Making Sense from Customer Reviews. *International Journal of Information Management*, 53.

Motwani, B. (2020). *Data Analytics using Python,* Wiley, 978-81-265-0295-0.

Nanda, M. & Randhawa, G. (2020). *Emotional Intelligence, Work-Life Balance, and Work-Related Well-Being: A Proposed Mediation Model.*

Naz, S., Li, C., Nisar, Q. A. & Rafiq, M. (2019). Linking Emotional Intelligence to Knowledge Sharing Behaviour: Mediating Role of Job Satisfaction and Organisational Commitment. *Middle East Journal of Management*, 6(3), 318–340.

Poecze, F., Claus, E. & Christine, S. (2018). Social Media Metrics and Sentiment Analysis to Evaluate the Effectiveness of Social Media Posts. *Procedia Computer Science*, 130, 660-666.

Ragini, J.R., Anand, Bhaskar, V.(2018). Big Data Analytics for Disaster Response and Recovery through Sentiment Analysis. *International Journal of Information Management.* 42, 13-24.

Rahman, S. A., AlOtaibi, F.A. & AlShehri, W.A. (2019). Sentiment Analysis of Twitter Data. International Conference on Computer and Information Sciences.

Rambocas, M. & Pacheco, B.G. (2018). Online Sentiment Analysis in Marketing Research: A Review. *Journal of Research in Interactive Marketing*, 12(2), 146-163.

Njoroge, C. N. & Yazdanifard, R. (2014). The Impact of Social and Emotional Intelligence on Employee Motivation in a Multigenerational Workplace. *Global journal of Management and Business Research*, 14(3), 31-36.

Rathore, A. & Ilavarasan P.V. (2020). Pre- and Post-Launch Emotions in New Product Development: Insights from Twitter Analytics of Three Products. *International Journal of Information Management*, 50, 111-127.

Saglam, F., Genc B. & Sever, H. (2019). Extending a Sentiment Lexicon with Synonym–Antonym Datasets. *Turkish Journal of Electrical Engineering and Computer Sciences,* 27, 1806 – 1820.

Salovey, P. & Mayer, J.D. (1990). *Emotional Intelligence,* 9(3), 185-211.

Schwartz, R.W. & Tumblin, T.F. (2002). The Power of Servant Leadership to Transform Health Care Organisations for the 21st-Century Economy. *Arch Surg*, 1419–27.

Schutte, M., Haggerty, H., Golden, C. & Dornheim (1998). *Development and Validation of a Measure of Emotional Intelligence*, Lauderdale.

Shanwal, V. K. (2004). *Emotional Intelligence: The Indian Scenario.* Indian Publishers Distributors.

Shayaa, S., Wai, P.S., Chung, Y.W., Sulaiman, A., Jaafar, N.I. & Zakaria, S.B. (2017). Social Media Sentiment Analysis on Employment in Malaysia. Proceedings of 8th Global Business and Finance Research Conference.

Sovie, M.D. & Jawad, A.F. (2001) Hospital Restructuring and its Impact on Outcomes: Nursing Staff Regulations are Premature. *The Journal of Nursing Administration,* 31, 588-600.

Sparrow, T. & Knight, A. (2006). *Applied Emotional Intelligence: The Importance of Attitudes in Developing Emotional Intelligence.* Jossey-Bass.

Tram, S. & O'Hara, L. (2006). Relation of Employee and Manager to Job Satisfaction and Performance. *Journal of Vocational Behaviour*, 68(3), 461-443.

Turetken, S. & Rogers T. (2020). A Comparative Assessment of Sentiment Analysis and Star Ratings for Consumer Reviews. *International Journal of Information Management*, 54.

Ugoani, J., Amu, C. & Emenike, K. O. (2015). Dimensions of Emotional Intelligence and Transformational Leadership: A Correlation Analysis. *Independent Journal of Management and Production*, 6.

Wagner, P., Ginger, M.C., Grant, M.M., Gore, J.R. & Owens, C. (2002). Physicians Emotional Intelligence and Patient Satisfaction. *Family Medicine*, 34, 750-754.

Wong, A. (2004). The Role of Emotional Satisfaction in Service Encounters. Managing Service Quality. *An International Journal.*

Yuliyanti, S., Taufik, D. & Heru, S. (2017). Sentiment Mining of Community Development Program Evaluation Based on Social Media. *Telecommunication Computing Electronics and Control*, 15 (4), 1858-1864.

Annexures:

ANNEXURE A: Sentiment Analysis for dimensions of Emotional intelligence

Sentiment Analysis for 'Social Skills':

Feature	TextBlob	Afinn	VADER
Accuracy	0.8479	0.8267	0.8429
Confusion Matrix	[38 111] [11 642]	[21 128] [11 642]	[39 110] [16 637]
Positive Sentiment	{'precision': 0.852589641434263, 'recall': 0.9831546707503829, 'f1-score': 0.9132290184921764, 'support': 653}	{'precision': 0.8337662337662337, 'recall': 0.9831546707503829, 'f1-score': 0.9023190442726633, 'support': 653}	{'precision': 0.8527443105756358, 'recall': 0.9754977029096478, 'f1-score': 0.9099999999999999, 'support': 653}
Negative Sentiment	{'precision': 0.7755102040816326, 'recall': 0.2550335570469799, 'f1-score': 0.3838383838383838, 'support': 149}	{'precision': 0.65625, 'recall': 0.14093959731543623, 'f1-score': 0.23204419889502761, 'support': 149}	{'precision': 0.7090909090909091, 'recall': 0.26174496644295303, 'f1-score': 0.3823529411764706, 'support': 149}

Sentiment Analysis for 'Empathy':

Feature	TextBlob	Afinn	VADER
Accuracy	0.8080	0.6796	0.6521
Confusion Matrix	[15 88] [66 633]	[29 74] [183 516]	[35 68] [211 488]
Positive Sentiment	{'precision': 0.8779472954230236, 'recall': 0.9055793991416309, 'f1-score': 0.891549295774648, 'support': 699}	{'precision': 0.8745762711864407, 'recall': 0.7381974248927039, 'f1-score': 0.8006206361520558, 'support': 699}	{'precision': 0.8776978417266187, 'recall': 0.698140200286123, 'f1-score': 0.7776892430278884, 'support': 699}
Negative Sentiment	{'precision': 0.18518518518518517, 'recall': 0.14563106796116504, 'f1-score': 0.16304347826086957, 'support': 103}	{'precision': 0.13679245283018868, 'recall': 0.2815533980582524, 'f1-score': 0.1841269841269841, 'support': 103}	{'precision': 0.14227642276422764, 'recall': 0.33980582524271846, 'f1-score': 0.20057306590257878, 'support': 103}

Sentiment Analysis for 'Intrinsic Motivation':

Feature	TextBlob	Afinn	VADER
Accuracy	0.7768	0.7955	0.7805
Confusion Matrix	[7 147] [32 616]	[7 147] [17 631]	[17 137] [39 609]
Positive Sentiment	{'precision': 0.8073394495412844, 'recall': 0.9506172839506173, 'f1-score': 0.8731396172927003, 'support': 648}	{'precision': 0.8110539845758354, 'recall': 0.9737654320987654, 'f1-score': 0.8849929873772792, 'support': 648}	{'precision': 0.8163538873994638, 'recall': 0.9398148148148148, 'f1-score': 0.8737446197991392, 'support': 648}
Negative Sentiment	{'precision': 0.1794871794871795, 'recall': 0.045454545454545456, 'f1-score': 0.07253886010362694, 'support': 154}	{'precision': 0.2916666666666667, 'recall': 0.045454545454545456, 'f1-score': 0.07865168539325842, 'support': 154}	{'precision': 0.30357142857142855, 'recall': 0.11038961038961038, 'f1-score': 0.16190476190476188, 'support': 154}

ANNEXURE B : Supervised Machine Learning Algorithms

Model	Accuracy of Training dataset	Accuracy of Test dataset	RMSE
Linear Regression Model	0.685	0.545	0.810
KNN Algorithm	0.715	0.572	0.728
Support Vector Machines	0.677	0.532	0.828
Random Forest	0.711	0.581	0.789
Gradient Boosting Model	0.749	0.675	0.723
Bagging Model	0.799	0.592	0.782