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Teachers emotional intelligence to predictive work performance using linear and non-linear models

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Abstract

Aim: Changes and reforms in educational systems worldwide have affected teachers' effectiveness in the classroom. However, despite these developments, evaluating and understanding how to predict a teacher's success is still difficult. In this study, which addresses a gap in the literature, the importance of emotional intelligence to teachers' professional success is explored. This study investigates the link between Emotional Intelligence (EI) and professional success along its four facets: emotional regulation, emotional awareness, emotional motivation, and social ability (relationship management).
Methodology: A total of 160 teachers from six different technical universities in Northeastern Nigeria were surveyed. Questionnaires were used to collect the data, then analyzed with an AI model (FFNN, LSSVM, NF, and MLR).
Findings: The models were assessed using the determination coefficient (R^2), root means square error (RMSE), and correlation coefficient (R). The result obtained from the simple models showed that Neuro-Fuzzy Sub Clustering Hybrid (NF-SCH) shows (R^2 = 0.8814502 and 0.8375132) both training and testing, the correctness of models has been improved, which increases the accuracy of the single models up to 17%, 18%, and 20% FFNN, MLR and LSSVM for calibration and up to 40%, 73% and 70% FFNN, MLR and LSSVM for verification respectively the results show a strong connection between emotional intelligence and work satisfaction.
Implications/Novel Contribution: Ultimately, this research contributes to the literature on emotional intelligence and has real-world implications for management in education administration and the Nigerian higher education system.
Keywords: EI, work performance, teachers, TVE, Artificial Intelligence (AI)

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INTRODUCTION

Educative systems worldwide are undergoing rapid transformations, with teachers' professional efficacy playing a pivotal role in these changes. It is difficult to discuss how to predict the success of teachers in light of these advancements, and it is even more difficult to assess them.

Teachers in vocational fields should be able to prepare their students for careers in their chosen fields through classroom instruction and hands-on training in the workplace. Since technical competency is the integration of knowledge and skill that underlies effective occupational performance, educators in technical and vocational fields must possess this skill set. A teacher's success can be gauged largely by looking at the instructor's personality, which is linked to their outlook, abilities, and expertise. It was argued by Blašková, Blaško, and Kucharčíková (2014) that teachers with personalities could foster positive relationships with students and improve their education. A teacher's character is directly related to his or her role in the classroom.

According to Ezeanokwasa, Nwachukwu, and Yaba (2014); Nedal and Alcoriza (2018), "Technical Vocational Educational and Training" (TVET) is a broad concept that encompasses, in addition to general education, the study of technology and associated sciences, as well as the activities, attitudes, understanding, and knowledge

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of occupations in various Socioeconomic fields. According to Amirian and Behshad (2016), TVET is actively seeking to acquire the knowledge and skills for the workplace to increase the prospects for long-term growth and development in the context of an increasingly knowledge-based economy, a dynamically changing workplace. Therefore, TVET prepares individuals with a wide range of knowledge, abilities, and mindsets that are now acknowledged as crucial to active participation in all aspects of work and life, not just technical and professional competence and its effects on organizational performance.

Personal competence in emotional intelligence is believed to allow people to accurately perceive their emotions, effectively regulate them, and respond sustainably, as suggested by the research presented in Rastegar and Memarpour (2009); Ismail, Nopiah, and Rasul (2020); Okpala, Omojuwa, Elenwo, and Opoko (2017). If you want to be an effective teacher, EI is a must-have quality.

It has been argued that high-quality professional development of teachers is critical for effective, high-quality teaching and educational attainment. In particular, it was decided that professors should always be working to improve their competence in their field and their awareness of and participation in relevant trends and developments in that field (Ismail et al., 2020). A growing body of research links EI to personal happiness, the quality of one's interpersonal relationships, and professional success. In education, EI has been linked to things like students' learning, academic success, pro-social activity, and, most recently, effective teaching (Dolev & Leshem, 2017). This study fills an intelligence gap in the existing literature by investigating the significance of EQ to educators' emotional success. As a result of these global changes, teachers' effectiveness in the classroom has changed. It is difficult to discuss how to predict the success of teachers in light of these advancements, and it is even more difficult to assess them. In light of this context, this study aims to predict the effectiveness of technical and vocational education teachers by examining the relationship between teachers' EI and factors like job performance and some demographic variables.

Background of Study

Skills and experience are the gears that drive a country's economic growth, and technical and vocational education and training (TVET) is the key to producing the innovative technologists that the world needs. Teachers in TVET programs, on the other hand, are stereotyped as having poor grades regardless of how well their instructors plan their lessons. Feelings, especially those of learning, play a significant role in organizations. Extensive studies have shown that an individual's level of success can be predicted by their unique blend of traits, including their background and aptitudes (such as general intelligence). Studies conducted recently in education have shown that more than just knowing what you're talking about is needed to be an effective teacher. To be effective educators, teachers must have specific personality characteristics, habits, and values (Amirian & Behshad, 2016). Therefore, this research will aggregate anecdotal accounts of student and parent satisfaction with a teacher's emotional intelligence based on the educator's professional effectiveness.

Problem Statement

TVET courses are designed with the student's success, and advancement in mind (Oz, 2015). Quality over quantity must be the mantra to achieve these ends. As a change, the world's educational systems have undergone significant transformations. Keeping up with the shifting demands placed on today's vocational educators is no easy feat. Because of this, they cannot empathize with their students and struggle to build rapport with students and coworkers. Their ability to deal with this type of situation depends critically on their grasp of emotional intelligence.

A person's emotional intelligence is a predictor of their productivity in the workplace, though this effect is only modest and indirect (Botey, Vaquero-Diego, & Sastre, 2020; Boyatzis & Saatcioglu, 2008; Castillo & Del Valle, 2017).

Educators' EI is crucial to their effectiveness as teachers and learners. Many different kinds of students will need help from TVET teachers throughout their training and education. While emotional intelligence has been widely hailed as a reliable predictor of success and leadership potential, few studies have provided empirical support for this claim. As a result, educators in Nigerian vocational and secondary schools now have access to technical teachers in EI. Those who taught the Technical and Vocational Education and Training (TVET) curriculum at teachers and universities in the Northeast were surveyed for this study.

Objectives of the study

The primary goal of this research is to examine and make predictions about the work performance of vocational teachers in TVET based on their emotional intelligence.

Research Questions

1. What are the technical and vocational teacher's EI competence in self-regulation, awareness, motivation, and social skill levels?
2. Does the EI of technical and vocational teachers predict their job performance?

Significance of the Study

The output of vocational teachers is the average benefit to the company throughout a given period, calculated from the sum of individual acts. Furthermore, the quantity and quality of each educator in a given classroom work, typically a particular production, suggests that the performance of an individual is generally determined by inspiration, will, and capacity to perform. A worker's character may reflect his or her success in the workplace. Professionally, EI workers thrive (Bose & Guha, 2018). Efficient teachers can better manage their emotions, thoughts, and state of mind in the classroom (Ghanizadeh & Moafian, 2011). It is an essential quality in a person who wants to live a long life. Relationships between work and personal life, the roles of vocational teachers Emotional intelligence prepares students for life's most challenging situations. Life can be balanced for learners if they learn to recognize and manage their emotions. This study aimed to evaluate teachers' emotional intelligence, and professional adaptability in higher vocational education schools (Bose & Guha, 2018). This is because there need to be more studies that directly correlate vocational teachers' emotional intelligence with student achievement. Therefore, this research will focus on the importance of emotional intelligence in predicting occupational success among vocational teachers.

LITERATURE REVIEW

Emotional Intelligence

First established is the definition of emotional intelligence as a form of social intelligence theory that referred an individuals effect of emotional and motivational response to act wisely in relationships (Thorndike & Colony, 1982). Until the 20th century, cognition and effect were often seen and studied as two separate mental mechanisms, and feelings were usually perceived to be less than they were and often interfered with (Salovey & Mayer, 1990). In the last two decades, emotional intelligence has become an area of science. This psychological concept is relatively recent, referring to the effective integration of thought and emotion (Dolev & Leshem, 2017). The EI can be generally described as the ability to understand and manage desires" Salovey and Mayer (1990) considered EI to be A collection of skills intended to lead to the proper evaluation and management of feelings in oneself and others, the successful control of emotions in oneself and others, and the use of experience to inspire, prepare and succeed one's life (Ghanizadeh & Moafian, 2011).

EI is also an umbrella term that covers a wide variety of interactional knowledge and skills. The aptitude to consider the feelings of others to build and maintain relationships between people, and most critically, our sense of social obligation, requires interpersonal skills and the ability to identify and realize individual motives and excitements is made up of intrapersonal skills (Katyal & Awasthi, 2005). In order to assess EI from this viewpoint, a knowledge, aptitude and skill-based model conceptualizing EI as a set of skills, independent of single characteristics or favored behavioral patterns, was proposed. The proponents of the EI capability models argued that the EI efficiency tests should be limited to a collection of emotion-related skills.

Boyatzis, Goleman, and Rhee (2000) EI viewpoint included five dimensions that concerned Self-awareness, inspiration for self-regulation, compassion and social skills. Despite differing viewpoints on the EI, concepts of emotional intelligence tend to be compatible rather than conflicting. The different conceptualizations of the EI precisely translate into an individual's intrapersonal and interpersonal self-relationship, i.e., a relationship with themselves a relationship with others (Oz, 2015). Emotional intelligence involved the process of assessing individual solely emotions and the emotions of counterpart. feelings correctly, processing emotional information and managing feelings to make life easier (Cordova, Dolci, & Gianfrate, 2015).

According to Mohamad and Jais (2016) "The ability to perceive feelings to boost thinking. It comprises the capacity to interpret emotions correctly, Accessing and generating emotions to support thinking; knowing emotions and emotional knowledge; reflectively managing emotions to encourage intellectual and emotional development.

Emotionality lies at the intersection of the individual and culture, since every person is connected to their communities by feeling themselves and by experiencing himself and emotions every day. This is why emotional analysis needs to take center stage in all disciplines because human beings have to be emotional (Mahasneh, 2016). EI is the capacity of people to comprehend and mark their own and others' own feelings, to use emotional knowledge to direct thoughts and behaves, to control and/or modify emotions to respond to their situations, or to accomplish their goal (s) (Bose & Guha, 2018). According to Debes (2021) It can be claimed that the EI expertise of school principals predicts good control over their expectations of self-efficacy, the study demonstrated that the EI competence and expectations of self-efficacy of school principals were high. The findings also found that women's expectations of self-efficacy were greater than those of men.

Work Performance/Efficiency of the Work

Job effectiveness is the accumulated expected value of the individual episodes of action that a person performs for the company over a normal period of time. Other than that, in terms of quality and quantity, it is also an individual output required from each employee in a specific job, which indicates that an individual performance is determined by motivation and desire most of the time (Mohamad & Jais, 2016).

TVET

Professional TVET is widely accepted as a crucial driving force for skills advancement. To achieve the goals and objectives of the program's continuation, TVET in Nigeria needs to improve and maintain global socio-economic growth and technological progress.

Skills and abilities are the driving force behind the Any country's economic growth and social progress (Goel, Hofman, Lahaie, Pennock, & Watts, 2010), and TVET (Technical Vocational Education and Training) is the key to training the labor force of technicians and entrepreneurs required for the evolving technological workforce (Ayonmike, Okwelle, & Okeke, 2015). TVET is used as a descriptive term for those fields of education, including, but not limited to, general education, the study of technology and related sciences and the growth of practical skills, attitudes, knowledge and information relating to careers in different sectors of economic and social life (Ayonmike et al., 2015). According to Mclean and David, TVET is concerned with acquiring knowledge and skills for the world of work to widen opportunities for sustainable empowerment and the socio-economic growth of the information economy and the rapidly evolving work climate. TVET therefore equips people not only with technological and vocational expertise, but also with a wide range of experience, skills and attitudes that are now recognized as necessary for good work and involvement in life (Ayonmike et al., 2015).

TVET has a range of priorities that vary from one country to another. In Nigeria, TVET is part of the structured framework that has integrated the education system into the three levels of education (primary, secondary and tertiary) in order to respond to the needs of the nation for skilled labor and to promote the economic status of individuals and nations in general. Therefore, because qualitative TVET is widely recognized as the basis of all growth, continuous improvement of the process is necessary for the achievement of the national TVET objectives, which in turn will lead to the achievement of the national goals of producing quality human resources for the self-sustaining national development (Ayonmike et al., 2015).

Nwachukwu et al. (2014) TVET is a critical and indispensable part of Nigeria's growth, such as improving System level governance, involve the social partnership in the planning of technical and vocational education and training it is the cornerstone upon which the socio-economic, technological and cultural development of a country must be founded this form of education according to Gleason et al. (2010) has the economic function of supplying trained personnel changing the person and allowing him to use complex technologies. Therefore, the focus is not only on the provision of professional staff for a static economy, but also for a dynamic one in particular changing societal needs for technological development.

MATERIAL AND METHODS

Instrumentation

This quantitative analysis is focused on Boyatzis et al. (2000) theory based on 15 items from Emotion Intelligent Object. These include Knowledge of oneself, self-regulation, inspiration, compassion, and social skills. Their use is limited to 15 items. The nine work output items are newly created items that are focused on work, teaching effectiveness and teaching value concepts (Ismail et al., 2020).

The researchers developed a self-administered Google Formula online questionnaire through (Google Doc, Mountain View) and LinkedIn. The survey included an introductory paragraph which informed study participants of their goals, the confidentiality of their responses and the freedom to refuse to respond or to withdraw altogether from the study. The questionnaire contains twenty-three (23) questions in four (4) items groups and three (3) demographic questions.

The participants were technical and vocational teachers who, if they had been interested in teaching at the technical college in recent years, were requested to complete the survey. Participants who did not adequately complete the survey were omitted from the dataset by matching email addresses for couples.

Creation of Model Proposed

Three distinct non-linear artificial intelligence-based models and a Single Linear Classical Model were used in this research, namely FFNN, LSSVM, Neuro fuzzy (NF) and Multi-Linear Regression (MLR), to be used for Pre-Linear Regression (MLR), to understand the scientific nature of data in the technical and vocational teachers work performance through their emotional intelligence. The computed values were evaluated using: a coefficient of determination (R^2), a mean Radical Square Mistake (RMSE) and a coefficient of correlation (*R*). The principal motivation for using different AI models is that the actions of various models must be understood and the decision must be made for the best model to Carry out the assignment via a Set of Basic Data. It collects the input parameters via Google Doc from survey questionnaires and preprocessed with statistical analysis and analysis of correlations. Until modeling, data has been normalized and is done in such a way that both The pace and precision of the models can be enhanced.

$$Y = 0.05 + \left(0.95 \times \left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right)\right) \tag{1}$$

Where the *y* = normalized data , *x* = calculated data, X_{min} = minimum and X_{max} = maximum respectively.

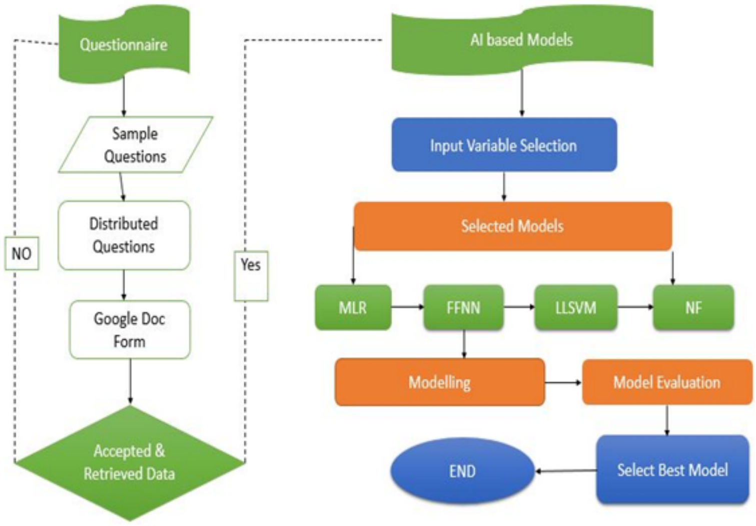

Figure 1. Proposed flow chart for data-driven processes

Feed Forward Neuronetwork (FFNN)

The important function of the feed forward neural network involves the fulfillment of information processing without needing the advanced mathematical model's architecture based on the intuitive relation between the neurons. As one of the most used ANNs, FFNN is a valuable tool that could capture a non-direct relation between output and input sources (Graham, White, Cologon, & Pianta, 2020). Equation (2) presents net feedback to the layers covered and yields. Like the traditional ANN, the FFNN consists of an input, one or more overlays and output layers in architecture (Figure 2)..

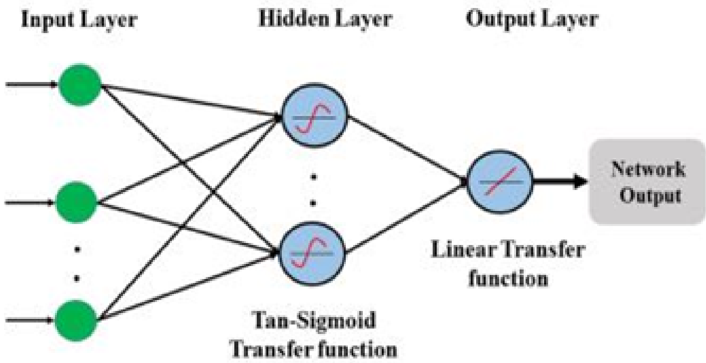

Figure 2. FFNN

$$y_i = \sum_{j=1}^{N} w_{ji} x_j + w_{io} \tag{2}$$

If *N* refers to the total number of nodes on the top layer of a node, *I* w_{ji} is the weight in the upper layers between *I* and *J* nodes; x_j is the contribution from *j* node; wio is the tendency in *I* node and y_i is a transmitter signal of *I* node.

Vector Machine Least- Square Support (LSSVM)

An improved algorithm for the Least-Squares Support Vector Machine (LSSVM) algorithm is the simple SVM, which offers a computational advantage (reduces the computational advantage), Burden) over the regular SVM by transforming the problem of quadratic optimization into a linear equation system (Zhou, Brown, Snavely, & Lowe, 2017). Instead of solving a quadratic problem by solving a linear sequence of equations, the LSSVM algorithm used in the SVM standard provides a solution. For both classification and regression, the LSSVM Challenge may be used for. More data on the model are available from (Zhou et al., 2017).

$$y = f(x) = w\phi(x_i) + b \tag{3}$$

Where φ(xi) indicates feature spaces, the input vector x is not - linearly mapped.

$$\text{Minimize: } \frac{1}{2}\|w\|^2 + C\left(\sum_{i}^{N}(\xi_i + \xi_i^*)\right) \tag{4}$$

Subject to:

$$\begin{cases} w_i\phi(x_i) + b_i - d_i \le \varepsilon + \xi_i^* \\ d_i - w_i\phi(x_i) + b_i \le \varepsilon + \xi_i^* \\ \qquad\qquad\qquad \xi_i, \xi_i^* \quad i = 1, 2, \ldots, N \end{cases}$$

$\frac{1}{2}\|w\|^2$ Where ^{2} " the norm of the vector weights and C refers to the regulatory constant. Figure 3 demonstrates the general conceptual model system of SVM. The parameters of the multipliers of Lagrange are known as ai and ai^*. In Equation vector w (3) can be determined after the problem optimization solution has been found.

$$w^* = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*)\,\phi(x_i) \tag{5}$$

The overall shape of LSSVM, therefore, informs Equation 6.

$$f(x, \alpha_i, \alpha_i^*) = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) K(x, x_i) + b \tag{6}$$

Where k (xi, xj) are the function of the Kernel, and b is the word bias. The common kernel function is radial basis function.

(Gaussian) it is expressed as: $k(x_1, x_2) = \exp\left(-\gamma \|x_1 - x_2\|^2\right)$ (7)

Where y is the kernel parameter.

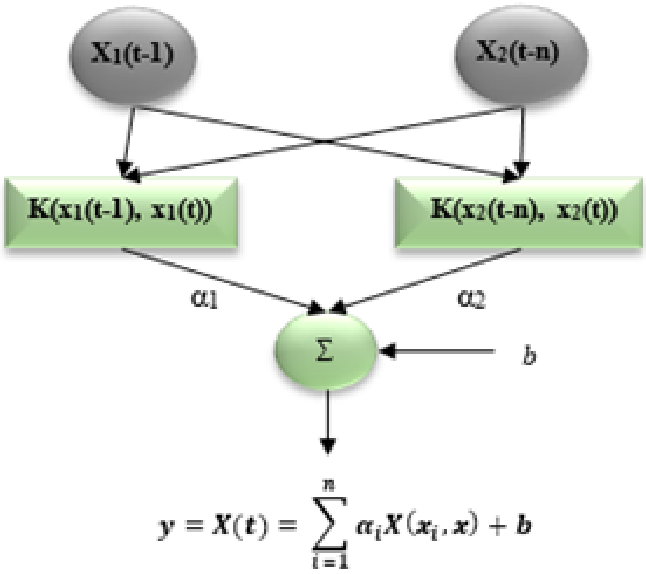

Figure 3. Schematic architecture of LSSVM

Fuzzy-Neuro (NF)

NF is a paradigm of learning as one of the algorithms for data intelligence. Neural network and FL capacity and unknown phenomena inherent in the systems are understood to be controlled. Due to its capacity, NF acts as a real-world estimator. True estimation functions. There are three forms of NF in general, namely Tsumoto, Sugeno, and Mamdani, with broader implementations of the Surgeon Method (Abba et al., 2017). There are various types of functions required for membership, such as Triangular, Sigmoid, Gaussian and Trapezoidal. The overall structure of NF reveals.

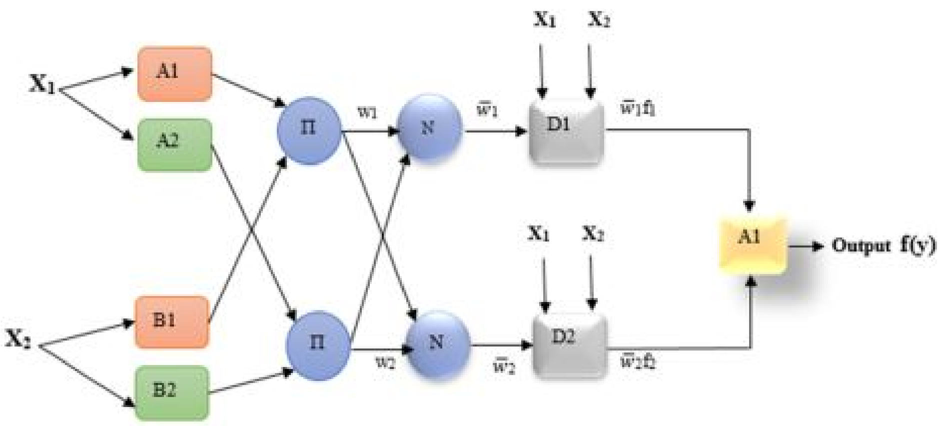

Figure 4. Neuro fuzzy (NF) schematic layout

If FIS is presumed to have two "x1" and "X2" inputs and one "f" output, the following rules apply to a first-order sugeno fuzzy.

$$\text{Rule 1 : if } \mu\left(x_1\right) \text{ is } A_1 \text{ and } \mu\left(x_2\right) \text{ is } B_1 \text{ then } f_1=p_1 x_1+q_1 x_1 \tag{8}$$

$$\text{Rule 2: if } \mu\left(\mathrm{x}_1\right) \text{ is } \mathrm{A}_2 \text{ and } \mu\left(\mathrm{x}_2\right) \text{ is } \mathrm{B}_2 \text{ then } \mathrm{f}_2=\mathrm{p}_2 \mathrm{x}_2+\mathrm{q}_2 \mathrm{x}_2 \tag{9}$$

Parameters A1, B1, A2, B2 are members of the x1 & x2 input feature. The outlet function parameters of the neuro fuzzy model are p1, q1, r1, p2, q2, r2. Five-layer neural network setup is accompanied by NF structures and formulation (Elkiran, Nourani, Abba, & Abdullahi, 2018).

Layer 1: Each node i is an adaptive node with a node feature.

$$Q_i^1=\mu_{Ai}(x) \text{ for } i=1,2 \text{ or } Q_i^1=\mu_{Bi}(x) \text{ for } i=3,4 \tag{10}$$

Where Q_i^1 is Affiliation grade for x or y input. Gaussian was the membership function selected because it had the lowest error in prediction.

Layer 2: Each rule between inputs is connected by the T-norm operator that functions as AND operator.

$$Q_i^2=wi=\mu_{Ai}(x)\cdot\mu_{Bi}(y) \text{ for } i=1.2 \tag{11}$$

Layer 3: The norm is labeled for each neuron, and the output is named Normalized firing strength.

$$Q_i^3=\bar{w}i=\frac{w_1}{w_1+w_2},1,2$$

Layer 4: Each node I is an adaptive node in this layer and performs the consequence of the rules.

$$Q_i^4=\bar{w}_i\left(p_1 x+q_1 y+r_1\right)=\bar{w}_i f_i \tag{12}$$

Layer 5: The total output of this layer is calculated as the sum of all incoming signals.

$$Q_i^5=\sum \bar{w}_i f_i=\frac{\sum_i w_i f_i}{\sum_i w_i} \tag{13}$$

Multi-Linear Regression (MLR)

Regression models generally expect the extent of the correlation between the parameters of inputs and outputs, as well as the relationship between them. Linear regressions are usually fitted using the least square approach, although other methods can be used equally, such as limiting the "lack of fit" in some of the standards or reducing the penalized variant loss of the least square function as for the ridge regression. Linear regression is primarily separately categorized into two major product divisions and simple linear regression. Linear regression is considered easy if a single input variable is used to predict the association between a single output. However, the purpose is to calculate the relationship between two or more input variables in order to evaluate a model, the variables of the unit criterion are known as multi-linear regression. MLR, in which each value of the input parameter is associated with the output variable value, is the most commonly used form of linear regression used in various fields of study. It is known that MLR shows a straight-line correlation in terms of excellent estimates of all data points concerning both the output and the target variables (Khademi, Jamal, Deshpande, & Londhe, 2016). The MLR model is, as shown in Equation (14).

$$y=b_0+b_1 x_1+b_2 x_2+\cdots b_i x_i \tag{14}$$

Where, is the value of the predictor of i_{th} b_a is the constant of regression, and bi the coefficient of the predictor i_{th} .

Evaluation Criteria for Data- Driven Models

Generally, for any form of data - driven approach, compared between expected and calculated values, work performance accuracy is assessed using different parameters. Herein analysis, the coefficient of the (R^2)

determination as an attraction - of - fit, coefficient of correlation (*R*) and statistical errors, For the evaluation of the models, RMSE was used:

$$R^2 = 1 - \frac{\sum_{J-1}^{N} \left[(Y)_{obs,j} - (Y)_{\text{com},j}\right]^2}{\sum_{j=1}^{N} \left[(Y)_{obs,j} - (\bar{Y})_{obs,j}\right]^2} \tag{15}$$

$$R = \frac{\sum_{i=1}^{N} \left(Y_{obs} - \bar{Y}_{obs}\right)\left(Y_{com} - \bar{Y}_{com}\right)}{\sqrt{\sum_{i-1}^{N} \left(Y_{obs} - \bar{Y}_{obs}\right)^2 \sum_{i=1}^{N} \left(Y_{com} - \bar{Y}_{com}\right)^2}} \tag{16}$$

$$RMSE = \sqrt{\frac{\sum_{i-1}^{N} \left(Y_{obsi} - Y_{comi}\right)^2}{N}} \tag{17}$$

Where N. $Y_{\text{absi}}\, Y$ and Y_{com} They are the number of data the data observed the normal value of the data observed and the calculated values. individually.

RESULTS AND DISCUSSION

The models used are (FFNN, NF, LSSVM and MLR) to analyse the technical and vocational teachers job performance through Emotional Intelligence EI, data were statistically analyzed before the models calibration as shown in Table 1. In general, in order to resolve common issues that can lead to incorrect analysis, mathematical analysis is used to explain data science.

Findings and to make reasonable decisions based on raw data, MATLAB 9.3 ($R^2$019a) was used for the Design of data-driven models for FFNN, NF and LSSVM models, in comparison, Excel 2016 was used to build the deterministic linear MLR model.

According Usman, Zarebanadkouki, Waseem, Katsoyiannis, and Ernst (2020) The ideal number of hidden layers is defined by the number of nodes ranging from (2n1/2+m) to (2n+1), while n is the number of input neurons and m is the number of output neurons. Therefore, three 3 input and one 1 output as the number of hidden neurons for the models in which age, gender and educational background are the input while work performance as the targets output variable.

Table 1: Statistical analysis

Variable	A	T-P	ED-B	G	M	WK-P
Mean	2.45	2.53125	2.49375	1.29375	20.545	5.100625
Std dev.	0.063195	0.0925366	0.086419	0.036121	1.311156	0.298423
Minimum	1	1	1	1	3	21
Maximum	5	5	5	2	16	85

A = Age, T-P =Teacher position, ED-B = Educational background,
G = Gender, M = motivation, WK-P = Work performance

Table 2: Spearman pearson correlation analysis

	A	T-P	ED-B	G	M	WK-P
A	1					
T-P	0.5360573	1				
ED-B	0.0464240	-0.2603619	1			
G	-0.0886813	-0.1054705	-0.1033348	1		
M	-0.2499159	-0.1514803	0.1340096	0.069970	1	
WK -P	-0.2660512	-0.2313116	0.2135854	0.058091	0.814650	1

A = Age, T-P =Teacher position, ED-B = Educational background,
G = Gender, M = motivation, WK-P = Work performance

Outcomes of Single Models

Table 3: Results of FFNN, NF, LSSVM and MLR models

	Calibration			Verification		
	R^2	R	RMSE	R^2	R	RMSE
FFNN- T	0.710344	0.8428192	0.1402932	0.43707108	0.6611134	0.0877513
FFNN- L	0.6157814	0.7847174	0.1615790	0.7984705	0.8935717	0.0981671
FFNN- P	0.6882031	0.8295800	0.1455565	0.47197619	0.6870052	0.0749081
MLR	0.6958412	0.8341710	0.1437626	0.0988621	0.3144201	0.0767337
LSSVM	0.6797925	0.8244953	0.1475066	0.1335450	0.36543125	0.0779352
NF - SCH	0.8814502	0.9388557	0.08975242	0.8375132	0.91515750	0.07767785

FFNN- T = Feed forward neural network Tansig, FFNN-L = feed forward neural network Logsin, FFNN-P = feed forward neural network Purelin, NF-SCH = NF- sub clustering hybrid.

Table 3 above presents the outcomes accuracy of the different models. It has been clearly seen from the comparative study of the models all four Models are predictable effectively the technical and vocational teachers job performance using the emotional intelligence. Among the four models, compared to the FFNN, NF, LSSVM and MLR models, provided a superior alternative to predicting competencies both in calibration and verification for R^2, R, and RMSE. Although the data involved in this analysis are standardized, the effect of the error would be lower associated to the non-standardized data.

However, the verification process of technical and vocational education teachers job/work performance, the forecast abilities based on goodness of fits (R^2) showed that The FFNN, MLR, and LSSVM models were outperformed by Neuro fuzzy (NF).

NF models as mentioned outperformed the other models by 17% for FFNN, 18% for MLR, and 20% for LSSVM.

While for verification the neuro fuzzy NF models outperformed the models by 40% for FFNN, 73% for MLR and 70% for LSSVM respectively.

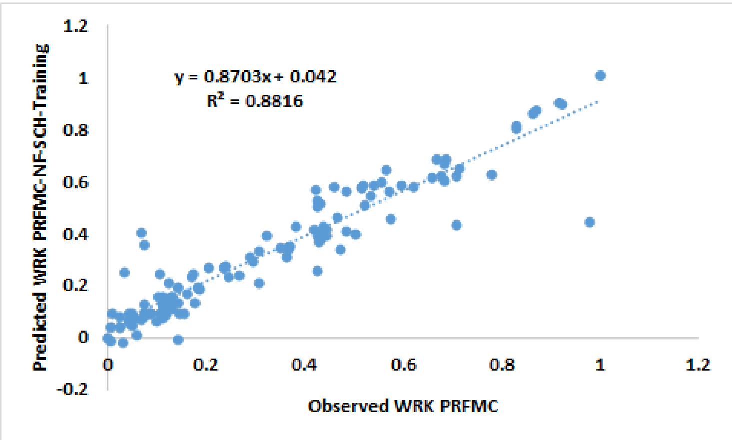

Figure 5. Scatter plots for NF-SCH training

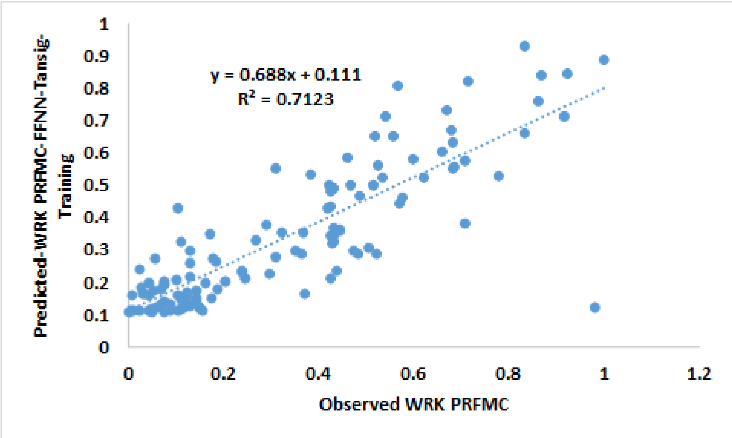

Figure 6. Scatter plots for FFNN -tansig training

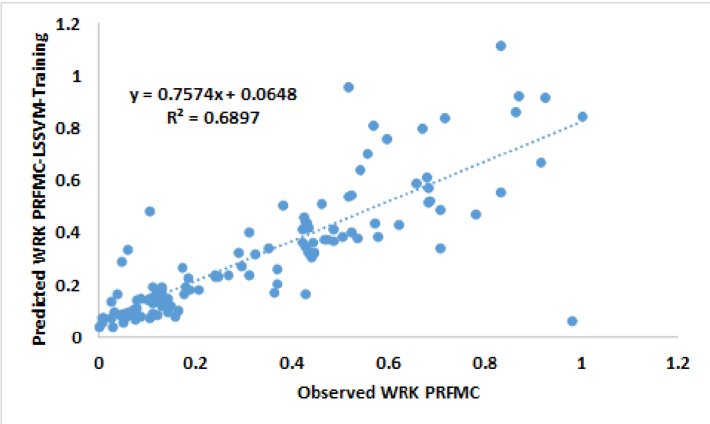

Figure 7. Scatter plot for LSSVM training

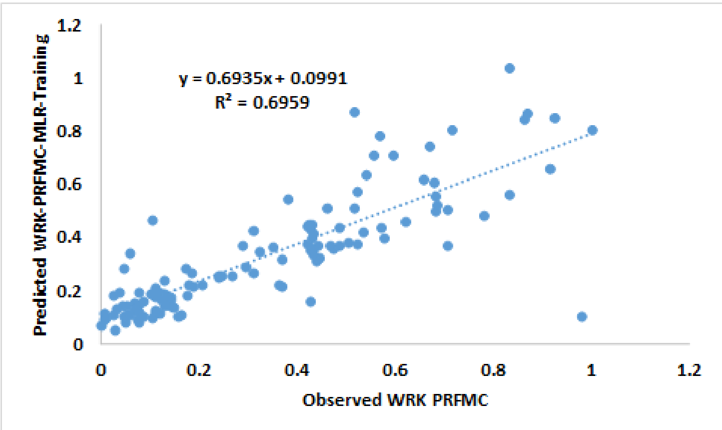

Figure 8. Scatter plots for MLR training

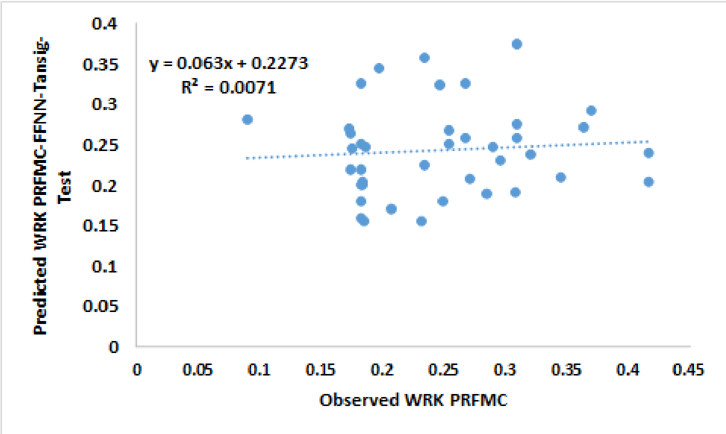

Figure 9. Scatter plots for NF- SCH- test

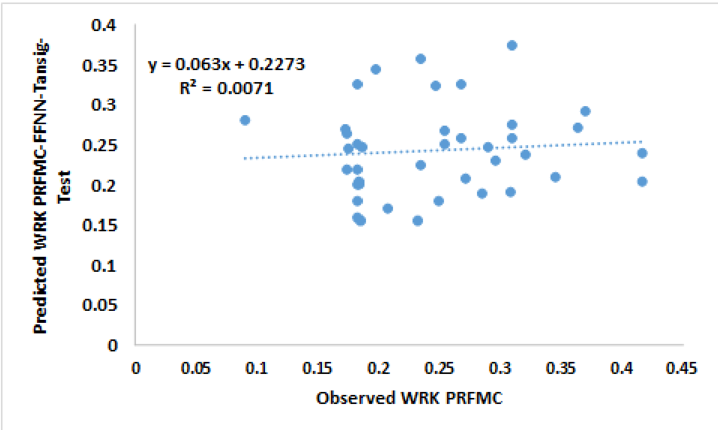

Figure 10. Scatter plots for FFNN-Tansig test

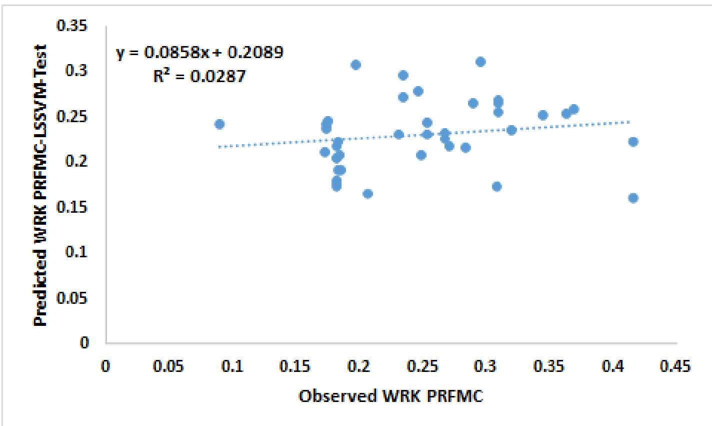

Figure 11. Scatter plots for LSSVM test

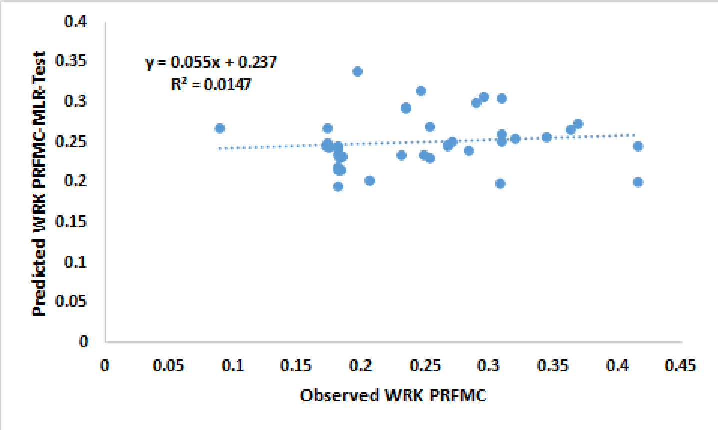

Figure 12. Scatter plots for MLR test

The dispersed scatter plot provides a further comparison of the findings as seeing in the figures above showing the work performance train and test for NF, FFNN, MLR and LSSVM models. The best model was related to the output error relationship in figures between the observed and expected values.

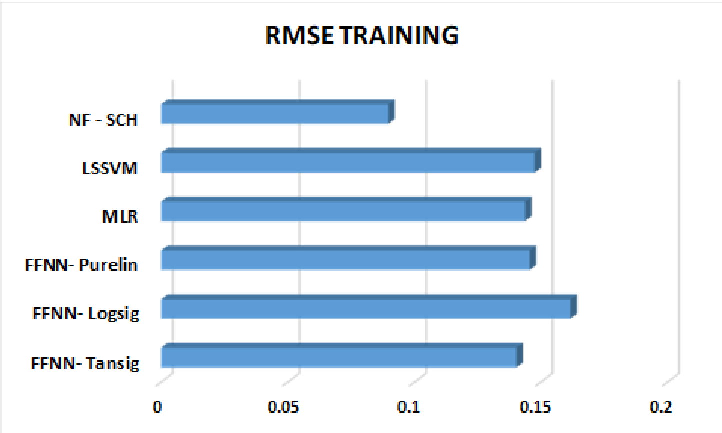

Figure 13. Bar Graph of RMSE training

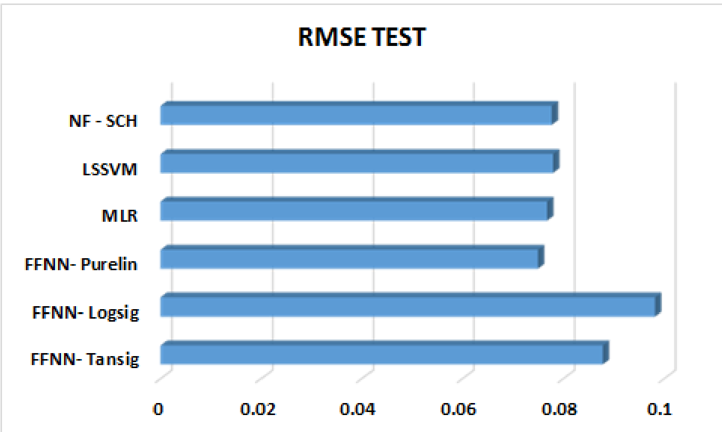

Figure 14. Bar graph of RMSE test

The bar graph in Figure 9 & 10 shows both the calibration and verification processes, all the error values were appropriate which indicates that neuro fuzzy NF is lower/less, this shows NF outperformed the other three models. This demonstrated that technical and vocational teachers work/ job performance. The artificial intelligence models AI cover the unpredictable and dynamic environment in the determination of job/work performance.

This was consistent with the (Cordova et al., 2015; Salovey & Mayer, 1990) studies which recorded an error value above 0.05. confirmed, however, Artificial neural network has satisfactory prediction whose attributed high correlation value model with the threshold of $R = 0.8$. Table 2 Conveyed that all artificial intelligence Used dependent models serve the expectation of prediction and therefore prove to be efficient in terms of the above objectives.

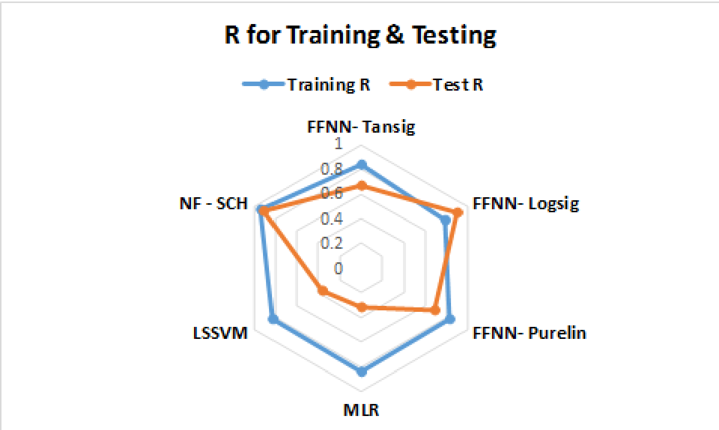

Figure 15. Radar diagram for various coefficients of variance determination

The above figure displays the radar charts for various coefficients of determination of variance. Three non-linear and one linear models for estimating the performance of technical and vocational teachers are the deciding values for the teaching and testing stages of the four models. Various studies such as (Bose & Guha, 2018) have shown that its high coefficient of correlation value is correlated with the strong output potential represented by models.

CONCLUSION

The main aim of this research was to test the performance of the wok in terms of self-awareness, self-regulation, impact, motivation, empathy and social skills based on models of artificial intelligence. Three non-linear single models with different transfer and membership functions, NF, FFNN, LSSVM and the classic linear regression model MLR, were used to predict job performance. After the input parameters were evaluated, it was concluded that NF delivers best outcomes in the preparation, testing and fostering phases with R^2 values of 0.8814502 and 0.8375152 and increased FFNN precision up to 17 percent, MLS 18 percent and LSSVM 20 percent and FFNN up to 40 percent, MLR 73 percent and LSSVM 70 percent respectively for the verification process (Graham et al., 2020).

To conclude, an aggregate comparison of the outcomes showed NF-SCH success in the private and classroom life to encourage efficiency both for teachers and the classroom, according to the proposal (Mahasneh, 2016) that training in emotional intelligence could also be used as a help to an emotionally smart teacher.

Finally, the study emphasizes the significance of emotional intelligence. The four domains of emotional intelligence (self-awareness, self-regulation, self-motivation, empathy, and social skills) tend to have a greater effect on teacher success. Emotional intelligence should be established and enhanced in a systematic and consistent manner in order to maintain high performance and competitive advantage.

Conflict of Interest

The author declares no interest of conflicts.

REFERENCES

Abba, M. L., Patil, N., Leupold, J. H., Moniuszko, M., Utikal, J., Niklinski, J., & Allgayer, H. (2017). Micrornas as novel targets and tools in cancer therapy. *Cancer Letters*, *387*(88), 84-94. doi:https://doi.org/10.1016/j.canlet.2016.03.043

Amirian, S. M. R., & Behshad, A. (2016). Emotional intelligence and self-efficacy of Iranian teachers: A research study on university degree and teaching experience. *Journal of Language Teaching and Research*, *7*(3), 548-560. doi:https://doi.org/10.1016/j.sbspro.2010.12.205

Ayonmike, C. S., Okwelle, P. C., & Okeke, B. C. (2015). Towards quality Technical Vocational Education and Training (Tvet) Programmes in Nigeria: challenges and improvement strategies. *Journal of Education and Learning*, *4*(1), 25-34. doi:https://doi.org/10.5539/jel.v4n1p25

Blašková, M., Blaško, R., & Kucharčíková, A. (2014). Competences and competence model of university teachers. *Procedia-Social and Behavioral Sciences*, *159*, 457-467. doi:https://doi.org/10.1016/j.sbspro.2014.12.407

Bose, S., & Guha, A. (2018). Emotional intelligence and professional adjustment of secondary school teachers. *International Journal of Research in Social Sciences*, *8*(4), 579-590.

Botey, M., Vaquero-Diego, M., & Sastre, F. (2020). Perceived emotional intelligence of university professors based on the nature of the subject taught. *Technological Forecasting and Social Change*, *161*, 120-292. doi:https://doi.org/10.1016/j.techfore.2020.120292

Boyatzis, R. E., Goleman, D., & Rhee, K. (2000). Clustering competence in emotional intelligence: Insights from the Emotional Competence Inventory (ECI). *Handbook of Emotional Intelligence*, *99*(6), 343-362.

Boyatzis, R. E., & Saatcioglu, A. (2008). A 20-year view of trying to develop emotional, social and cognitive intelligence competencies in graduate management education. *Journal of Management Development*, *27*(1), 92-108. doi:https://doi.org/10.1108/02621710810840785

Castillo, M. Á. S., & Del Valle, I. D. (2017). Is emotional intelligence the panacea for a better job performance? A study on low-skilled back office jobs. *Employee Relations*, *39*(5), 683-698. doi:https://doi.org/10.1108/ER-11-2016-0216

Cordova, A., Dolci, J., & Gianfrate, G. (2015). The determinants of crowdfunding success: Evidence from technology projects. *Procedia-Social and Behavioral Sciences*, *181*, 115-124. doi:https://doi.org/10.1016/j.sbspro.2015.04.872

Debes, G. (2021). The predictive power of emotional intelligence on self efficacy: A case of school principals. *International Online Journal of Education and Teaching*, *8*(1), 148-167.

Dolev, N., & Leshem, S. (2017). Developing emotional intelligence competence among teachers. *Teacher Development*, *21*(1), 21-39. doi:https://doi.org/10.1080/13664530.2016.1207093

Elkiran, G., Nourani, V., Abba, S., & Abdullahi, J. (2018). Artificial intelligence-based approaches for multi-station modelling of dissolve oxygen in river. *Global Journal of Environmental Science and Management*, *4*(4), 439-450. doi:https://doi.org/10.22034/GJESM.2018.04.005

Ezeanokwasa, F., Nwachukwu, O. P., & Yaba, L. (2014). Effective entrepreneurship skills in reducing unemployment through small business innovation in Nigeria. *Journal of Information and Knowledge Management*, *4*(11), 97-102.

Ghanizadeh, A., & Moafian, F. (2011). Critical thinking and emotional intelligence: Investigating the relationship among EFL learners and the contribution of age and gender. *Iranian Journal of Applied Linguistics*, *14*(1), 23-48.

Gleason, K. M., McDaniel, M. R., Feinglass, J., Baker, D. W., Lindquist, L., Liss, D., & Noskin, G. A. (2010). Results of the Medications at Transitions and Clinical Handoffs (MATCH) study: An analysis of medication reconciliation errors and risk factors at hospital admission. *Journal of General Internal Medicine*, *25*(5), 441-447. doi:https://doi.org/10.1007/s11606-010-1256-6

Goel, S., Hofman, J. M., Lahaie, S., Pennock, D. M., & Watts, D. J. (2010). Predicting consumer behavior with web search. *Proceedings of the National Academy of Sciences*, *107*(41), 17486-17490. doi:https://doi.org/10.1073/pnas.1005962107

Graham, L. J., White, S. L., Cologon, K., & Pianta, R. C. (2020). Do teachers years of experience make a difference in the quality of teaching? *Teaching and Teacher Education*, *96*, 10-20. doi:https://doi.org/10.1016/j.tate.2020.103190

Ismail, K., Nopiah, Z. M., & Rasul, M. S. (2020). Emotional intelligence and work performance among vocational teachers. *Journal of Technical Education and Training*, *12*(3), 106-117. doi:https://doi.org/10.30880/jtet.2020.12.03.011

Katyal, S., & Awasthi, E. (2005). Gender differences in emotional intelligence among adolescents of Chandigarh. *Journal of Human Ecology*, *17*(2), 153-155. doi:https://doi.org/10.1080/09709274.2005.11905771

Khademi, F., Jamal, S. M., Deshpande, N., & Londhe, S. (2016). Predicting strength of recycled aggregate concrete using artificial neural network, adaptive neuro-fuzzy inference system and multiple linear regression. *International Journal of Sustainable Built Environment*, *5*(2), 355-369. doi:https://doi.org/10.1016/j.ijsbe.2016.09.003

Mahasneh, A. M. (2016). Emotional intelligence as a predictor of teacher sense of self-efficacy among student teachers in Jordan. *North American Journal of Psychology*, *18*(1), 1-10.

Mohamad, M., & Jais, J. (2016). Emotional intelligence and job performance: A study among Malaysian teachers. *Procedia Economics and Finance*, *35*, 674-682. doi:https://doi.org/10.1016/S2212-5671(16)00083-6

Nedal, O. A., & Alcoriza, M. G. O. (2018). Challenges in education: The untold story of students in Lanao Kapanglao, Glan, Sarangani province. *Journal of Advances in Humanities and Social Sciences*, *4*(3), 118-126. doi:https://doi.org/10.20474/jahss-4.3.1

Nwachukwu, J. C., Srinivasan, S., Bruno, N. E., Parent, A. A., Hughes, T. S., Pollock, J. A., . . . Garcia-Ordonez, R. D. (2014). Resveratrol modulates the inflammatory response via an estrogen receptor-signal integration network. *Elife*, *3*(6), 1-10. doi:https://doi.org/10.7554/eLife.02057.001

Okpala, O. R., Omojuwa, Y., Elenwo, C. G., & Opoko, P. A. (2017). Sustainable urbanization: Investigating problems encountered in uncontrolled urban growth in Nyanya-A suburb of Abuja, Nigeria. *International Journal of Humanities, Arts and Social Sciences*, *3*(1), 13–19. doi:https://doi.org/10.20469/ijhss.3.20003-1

Oz, H. (2015). Emotional intelligence as a predictor of l2 communication. *Procedia-Social and Behavioral Sciences*, *186*, 424-430. doi:https://doi.org/10.1016/j.sbspro.2015.04.117

Rastegar, M., & Memarpour, S. (2009). The relationship between emotional intelligence and self-efficacy among Iranian EFL teachers. *System*, *37*(4), 700-707. doi:https://doi.org/10.1016/j.system.2009.09.013

Salovey, P., & Mayer, J. D. (1990). Emotional intelligence. *Imagination, Cognition and Personality*, *9*(3), 185-211. doi:https://doi.org/10.2190/DUGG-P24E-52WK-6CDG

Thorndike, A., & Colony, R. (1982). Sea ice motion in response to geostrophic winds. *Journal of Geophysical Research: Oceans*, *87*(C8), 5845-5852. doi:https://doi.org/10.1029/JC087iC08p05845

Usman, M., Zarebanadkouki, M., Waseem, M., Katsoyiannis, I. A., & Ernst, M. (2020). Mathematical modeling of arsenic (v) adsorption onto iron oxyhydroxides in an adsorption-submerged membrane hybrid system. *Journal of Hazardous Materials*, *400*(5), 123-221. doi:https://doi.org/10.1016/j.jhazmat.2020.123221

Zhou, T., Brown, M., Snavely, N., & Lowe, D. G. (2017). Unsupervised learning of depth and ego-motion from video. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, California, CA.*