International Journal of Advanced Multidisciplinary Research
ISSN: 2393-8870
www.ijarm.com
(A Peer Reviewed, Referred, Indexed and Open Access Journal)
DOI: 10.22192/ijamr Volume 10, Issue 5 -2023

Research Article

DOI: http://dx.doi.org/10.22192/ijamr.2023.10.05.005

A Machine Learning Model for Prediction of Factors Affecting Internet-Based Learning Technologies

Dr. Yakubu Bala Mohammed [1*]
Abubakar Tatari Ali Polytechnic, Department of Computer Science, Nigeria, Bauchi-State, Jos Road 0094, Nigeria.
E-mail: *mohammedbala0079@gmail.com*

Mohammed Bula [1]
Abubakar Tatari Ali Polytechnic, Department of Computer Science, Nigeria, Bauchi-State, Jos Road 0094, Nigeria.
E-mail: *mbgiade@gmail.com*

Keywords

Internet-based learning,
machine learning,
e-Learning,
LMS.

Abstract

With recent advancements in the areas of internet technologies and learning management systems (LMS), the learning process has become more efficient and effective as learners can learn anywhere, anytime using devices via the internet, especially in advanced nations. However, these systems are either not deployed or fully utilized in majority of African colleges which led to total schools' closure during pandemic period or national exercises such as Covid-19 and national elections. To address these problems, the study examined the factors affecting internet-based technologies using two machine learning methods (ML); "Adaptive neuro-fuzzy Inference system" (ANFIS), and "Feed-forward neural network" (FFNN). Data obtained from 896 Nigerian tutors/learners was used in testing and training the study ML models. Results of the study show that the ML models predicted the effects of the study inputs on internet-based learning (IBL) technologies with higher precision (NSE > 0.93). But the ANFIS model outperformed the FFNN model with (NSE > 0.96). Furthermore, results of the study found learners' encouragement (LE), and students ration (SR) to be the most dominant factors affecting IBL in the research area with correlation coefficient of > 0.98, while systems availability (SA), and ease of usage (EU) were discovered to have less influence on IBL in the research area with correlation coefficient of < 0.95. Lastly, the study explained the implications of the study results for both practitioners and researchers.

1. Introduction

In recent past, research (Alghamdi & Bayaga, 2016; Cavus et al., 2021b) have shown that different Internet-based Learning (IBL) technologies such as WebCT, Moodle, 360Learning, eFront, ProProfs and Edmodo etc., have complemented the conventional methods of teaching, i.e., “face-to-face and hybrid/blended teaching-learning processes”, especially during the Covid-19 pandemic. LMS is defined as “software platforms embedded with instructional tools that allow instructors to organize teaching content and engage students in their learning processes via the internet” (Rani et al., 2016). Nowadays, LMS offers virtual means of improving communication between instructors and learners, and faster effective and speedy learning process. Though, internet-based learning offers several benefits and features to institutions, especially in advanced nations such as UK, China, US, Russia, France etc. However, IBL implementation and usage are beyond stakeholders’ expectations in developing nations, especially Nigeria as only few colleges are making efforts to deploy different IBLs for teaching and learning. But even those that succeeded in deploying IBL, the systems are not fully utilized by both tutors and learners. Thus, compelling schools to close during national exercises such as general elections, population census, and pandemic periods e.g., during Covid-19.

Mohammed and Karagozlu (2021) and Yakubu et al. (2020) in their studies that “successful integration of technology in teaching and learning process depends not only on systems availability/ease of use but also on students ratio and instructors acceptance”. Also, Cavus et al. (2021b) in their study stressed that factors affecting internet-based learning are usually investigated using conventional models such as the “Technology Acceptance Model (TAM)”, and “Unified Theory of Acceptance and Use of Technology (UTAUT)” which are time-taking, and occasionally produced imprecise results. Thus, the need to further investigate the issues responsible for slow the growth of internet-based learning technologies in developing nations with special attention to Nigeria using more robust approach such as Machine Learning (ML) in order to obtain more accurate results. Therefore, the aim of this present study is; (a) to investigate the factors affecting internet-based learning technologies among tutors and learners and (b) to determine the correlation between the study input and internet-based learning technologies in the research location using two machine learning algorithms i.e., “Feed-forward neural network (FFNN)” and “Adaptive Neuro-Fuzzy Inference System (ANFIS)” due to their prediction ability. By carrying out experimental research among tutors and learners, the study offered interesting findings regarding factors affecting internet-based learning technologies, in our case LMS in the research location.

2. Materials and Methods

2.1. Internet-based learning technologies challenges

Internet-based learning technologies, specifically “Learning Management Systems (LMS) offer several functions and tools such as online discussions and group chats, course content handling tools, and evaluation and grading tools to support both learners and tutors in the teaching process (Fathema et al., 2015). Though, colleges in advanced nations invested a lot of resources in LMS deployment, and the results have begun to manifest in their educational sectors. However, LMS deployment and patronage continue to suffer a serious setback in emerging countries like Nigeria. For instance, Yakubu et al. (2020) argued that systems availability and perceived usefulness significantly affect the development of LMS in Nigerian colleges, thus the need for stakeholders to do more in the areas of systems provision and enlightenment. Another study conducted by Cavus et al. (2021b) in the same area found resources that support LMS implementation such as internet, electricity, and computers to be the main issues influencing internet-based learning technologies. The authors argued that facilitating conditions were the main reasons for LMS slow progress not only in Nigeria but also in other African nations. Yakubu et al. (2018) in their study found lack of willingness from learners' point of view and internet connectivity and speed to be among the key issues affecting various internet-based learning in Sub-Saharan Africa. The authors stressed the need for high-speeds internet connection in order to allow the learners to access learning materials anywhere, anytime using any device. Another research conducted by Gunawan et al. (2019) discovered that "majority of faculty members in tertiary institutions prefer the conventional teaching approach compared to modern computer-based learning technologies such as LMS. Thus, affects the fullest usage and progress of different internet-based learning management systems deployed by the colleges (Nizar, 2020).

Alhadreti (2021) argued that "there is an increasing concern among tutors and learners concerning the quality of the interface and how tasks are completed in these systems". Thus, stressed the need for developers to improve the quality of LMS interface in order to allow usersto carry out their tasks, in an efficient, effective and pleasing manner. Furthermore, it was discovered by prior eLearning studies that, "large number of LMS functions were not utilized by the users, this is because some functions are more frequently utilized than others"(Chen et al., 2021; Fathema et al., 2015; Mohammadi et al., 2021; Sharifov et al., 2021). For instance, Sharifov et al. (2021) in their research found grading and document uploads to be the most frequently utilized functions compared to other functions of various LMS deployed.

2.2. Technology acceptance models in internet-based learning

Acceptance and progress of new innovations e.g., Internet-based learning technologies are usually inspected using classical approaches such as DeLone and McLean (2003) "model of Information Systems Success (D&M)", Liao et al. (2007) "revised Theory of Planned Behaviour (TPB)", and Davis et al. (1989) "Technology Acceptance Model (TAM)". Bailey et al. (2022) and Cavus et al. (2021b) in their studies argued that majority of internet-based learning management systems "were examined using "conventional models such as TAM, D&M, and TPB models. Though, these and other conventional approaches still remain useful and valid. However, Cavus et al. (2021a) and Umar et al. (2022) argued that "classical approaches consumed a lot of time, and sometimes produced imprecise predictions compared to machine learning (ML) techniques. Thus, the need to employ different ML approaches so that accurate and reliable prediction can be obtained with regards to the main issues affecting internet-based learning technologies.

3. Methods

3.1. Research design

In contrast to prior LMS studies, the study "data collection tools" contains four inputs; learners' encouragement (LE), student's ratio (SR), systems availability (SA), and ease of use (EU), for predictions of factors affecting internet-based learning technologies in the study area. All the inputs were validated and tested using confirmatory and exploratory factors analysis i.e., Cronbach Alpha (CA) andComposite reliability (CR) all of which confirmed that there is a high level of internal consistencies among the inputs as the results were all > 0.80 which is an outstanding result (Cavus et al., 2021a).

3.2. Datasets

Primary data were used for this study, the main purpose of collecting primary data is to develop machine learning (ML) models capable of estimating the influence of the study inputs on various internet-based learning technologies with higher accuracy. The study dataset comprises of four parameters; learners' encouragement (LE), students' ratio (SR), systems availability (SA), ease of use (EU), and participants' demographic details such as level of education, gender, and age. Effects of the study inputs on internet-based learning technologies were assessed using two ML algorithms i.e., “Feed-forward neural network (FFNN)” and “Adaptive Neuro-Fuzzy Inference System (ANFIS)” due to their precision level. A total of 896 datasets were obtained from 5 colleges in northern Nigeria comprising of 497 (55%) males and 399 (45%) females.

3.3. Machine learning techniques

Though, previous eLearning studies succeeded in itemizing some of the factors affecting internet-based learning technologies in developing nations using different classical models such as TAM, D&M, and TPB. However, Thanh et al. (2022) argued that classical methods e.g., “Least squares, Pearson correlation, and Partial least squares” occasionally produced imprecise results compared to ML techniques such as “Artificial neural network (ANN), Adaptive Neuro Fuzzy Inference System (ANFIS), Feed-forward neural network (FFNN), and Support Vector Regression (SVR)” due to their precision in making predictions. Therefore, this research used two different ML methods i.e., FFNN and ANFIS to predict the effects of the study inputs on internet-based learning technologies in the research location.

3.3.1. ANN model

Nowadays, Artificial Neural Networks (ANN) are used to “simulate and perform functional features similar to the biological neural network of the human brain”(Hussain et al., 2021). Thus, offers computers the ability to learn relationships among variables, and makes them ideal for predicting the correlation between the study inputs and outputs.Scholars in different areas e.g., Computer science, Economics, Engineering, and neurosciences use ANN to estimate the relationship that exists between the inputs and output variables. Algorithm of the study FFNN is offered in **Figure 1,** below.

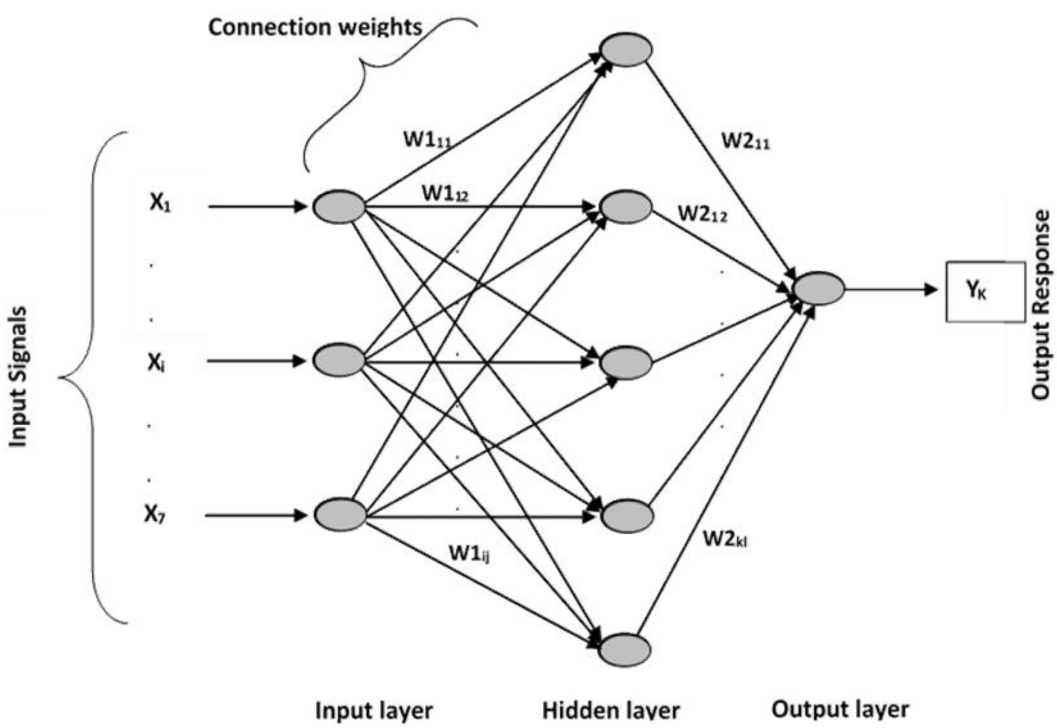

Figure 1: Algorithm of the study three-layer FFNN with input, hidden, and single output layer(Hussain et al., 2021).

3.3.2. ANFIS model

As displayed in **Figure 2**, the proposed ANFIS algorithm of the study consists of five layers; a) the fuzzifying layer that conveys the inputs LE, SR, SA, and EU, and regulates their functional associations, b) the inference layer that generates network rules shooting strengths, c) Normalizing layer that regularized the shooting strengths of each of theinputs so that a balance shooting strengths among the inputs can be maintain, d) de-fuzzifying layer that is responsible for conveying the regularized inputs into the fifth layer, and d) the aggregation layer that performed the functions of obtaining model estimation (i.e., prediction results), for this study effects of the study inputs (LE, SR, SA, and EU) on internet-based learning technologies. ANFIS algorithm of the study is offered in **Figure 2.**

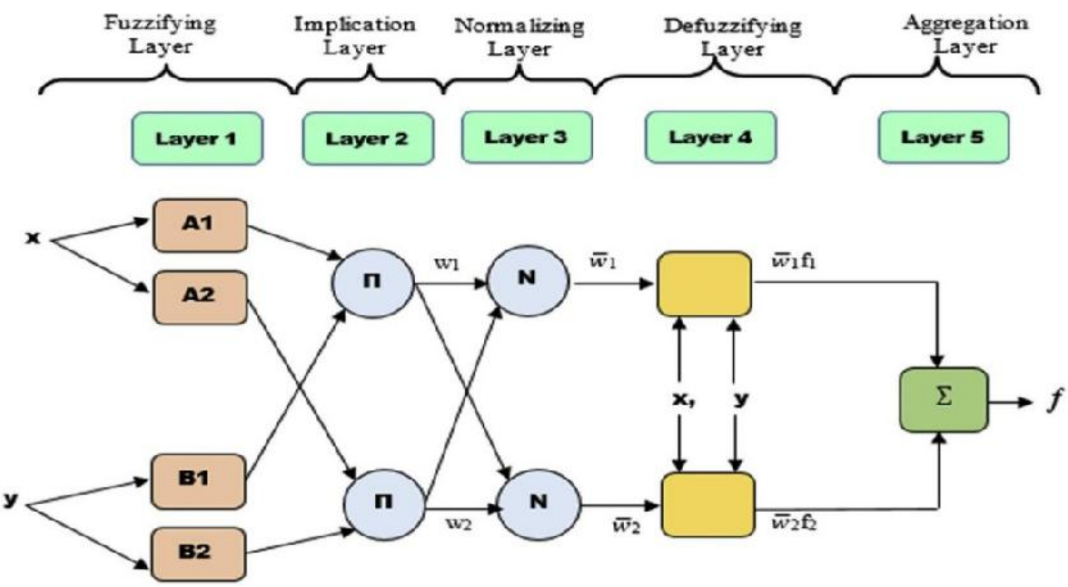

Figure 2: Algorithm of the study proposed ANFIS model.

3.4. Models' performance evaluation criteria

The Dataset for the study was standardized so that data with higher values do not overshadow those with lower values. Thus, the study dataset was standardized to range between 0 and 1 using equations 1,

$$N_{norm} = \frac{N - N_{min}}{N_{max} - N_{min}} \quad (1).$$

while performance of the employed ML models (i.e., FFNN and ANFIS) was measured using three statistical indices; "Ranking mean (RM)", "Nash-Sutcliffe efficiency (NSE)", and "relative Root mean square error (rRMSE)". The three evaluation indices were explained using equations 2 – 4.

$$\text{rRMSE} = \frac{\sqrt{\frac{\sum_{i=1}^{n}\left(N_{obs_i} - N_{pre_i}\right)^2}{n}}}{\frac{1}{N}\sum_{i=1}^{n}\left(N_{obs_i}\right)} \times 100 \quad (2)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(N_{obs_i} - N_{pre_i}\right)^2}{\sum_{i=1}^{n}\left(N_{obs_i} - \overline{N_{obs_i}}\right)^2} \quad (3)$$

$$R = \frac{1}{n}\sum_{n}^{1} rank_i \quad (4)$$

Algorithm of the study proposed machine learning method is presented in **Figure 3**.

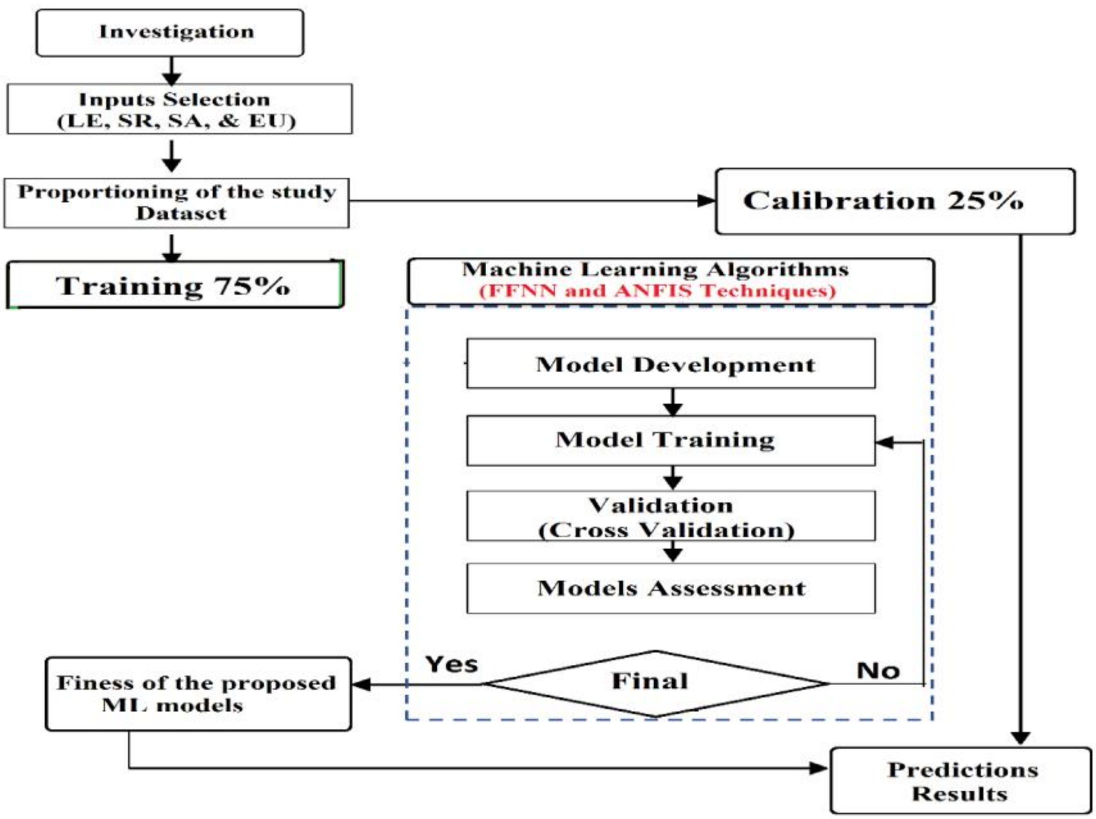

Figure 3: Flow diagram of the study proposed machine learning approach.

4. Results and Discussion

Prediction results of the research proposed ML models concerning the influence of the selected inputs (i.e., LE, SR, SA, and EU) on internet-based technologies in the study area, and input parameters ranking results were offered in the following section.

4.1. Prediction results

Two ML models (i.e., FFNN and ANFIS) were employed for estimation of the study inputs (LE, SR, SA, and EU) influence on internet-based learning technologies in the research location. Predictions made by each of the research ML models are presented in **Table 1**.

Table 1: Performance results of the study ML models

MODELS	Training			Testing		
	NSE	rRMSE	RM	NSE	rRMSE	RM
ANFIS	0.9436	2.1025	1	0.9612	4.0632	1
FFNN	0.9223	3.5108	2	0.9301	4.1103	2

As shown in **Table 1** above, concert of the research 2 ML models in training and testing was evaluated and graded using 3 valuation metrics of "Nash-Sutcliffe efficiency (NSE)", "Ranking mean (RM)", and "relative Root mean square error (rRMSE)". As seen in **Table 1**, it can be said that both the study ML models i.e., FFNN and ANFIS predicted the influence of the study inputs (LE, SR, SA, EU) with higher precision as both models have an NSE value of 0.9612 and 0.9301 in the testing stage which are very close to the study target of 1. The result clearly indicates a strong correlation between the learner's encouragement (LE), student's ratio (SR), availability of internet-based learning systems i.e., systems availability (SA), and systems ease of usage (EU) in the research area. This result is reinforced by the findings of Aryani et al. (2022) and Funda and Jali (2022) who argued that "learner encouragement and students perception on how easy to use the available systems may have negative effects on internet-based learning technologies not only in African nations but also other developing nations. Also, the results affirm the superiority of machine learning (ML) models compared to classical models such as TAM and D&M in terms of forecasting ability as the models rRMSE values stood at < 5 in both testing and training stages. This sentiment was supported by the argument of Cavus et al. (2021b) and Nourani et al. (2020). The authors stressed that ML techniques are more reliable and robust compared to conventional approaches. Based on the models' prediction results, tutor/students' ratio (SR) and lack of access to eLearning systems (SA) are other factors hindering internet-based learning in the research area. These findings are in agreement with the findings of Gomersall and Floyd (2022) and Tsimba et al. (2022), the researchers claimed that "teachers/students ration will have a significant effect on internet-based learning technologies. The authors claimed that a higher teachers/students' ratio may negatively affect the learning process in an online setting and vice-versa. Likewise, non-availability or inadequate provision of eLearning systems may affect both tutors'/learners' interest in internet-based learning technologies. Thus, the need for college administrators to do more in the areas of resources that enable internet-based learning. Though, both the study ML models predicted the effects of LE, SR, and SA, on internet-based learning technologies with higher accuracy. But the ANFIS model outclassed the FFNN model as it was ranked first by the "Ranking Mean (RM) in terms of precision.

Having gotten the prediction results from the research ML models regarding the correlation between the study inputs and internet-based learning technologies, the Taylor graph was used to determine the effect of each of the separate inputs i.e., LE, SR, SA, and EU on internet-based learning technologies. The graph offers accurate and consistent means of measuring inputs level of significance or in other words, assessing the maximum effects of each of the study inputs on the study output by at least three arithmetic metrics i.e., Standard deviation (sd), Correlation coefficient (NSE), and Root means square error (RMSE) in a pictorial way to evaluate the effect of each of the study inputs. As shown in **Figure 4**, the correlation among the fields is denoted by the "test field of the azimuthal spot, while the standard deviation of the pattern is the radial measured from the origin, and the RMSE cantered value is proportional to the distance between estimated and actual fields with identical units as the standard deviation in the graph"(Moazenzadeh et al., 2018). Thus, when the RMSE values reduce, the correlation between the variables increases and vice versa.

Therefore, input with a high level of significance or effects are the ones usually detached by reference points with the "correlation coefficient equivalent to 1, and parallel abundancy of diversities which are compared with the observation points"(Tikhamarine et al., 2019).

Based on the research Taylor results as shown in **Figure 4**, learners' encouragement (LE) is the most significant factor affecting internet-based learning in the study area with correlation coefficient (Cc > 0.98), followed by students' ratio (SA) with (Cc > 0.96). The two results were supported by the findings of Mahfoodh and AlAtawi (2020), the authors stressed that "lack of motivation and high tutor/students ration may affect internet-based learning not only in emerging nations but also in advance states". Furthermore, the Taylor results clearly show that "perceived ease of use (EU), and systems availability" has less impact on both tutors/learners in the research area as both the variable has a (Cc < 0.95) compared to LE and SR. The Taylor inputs evaluation results is offered in **Figure 4**.

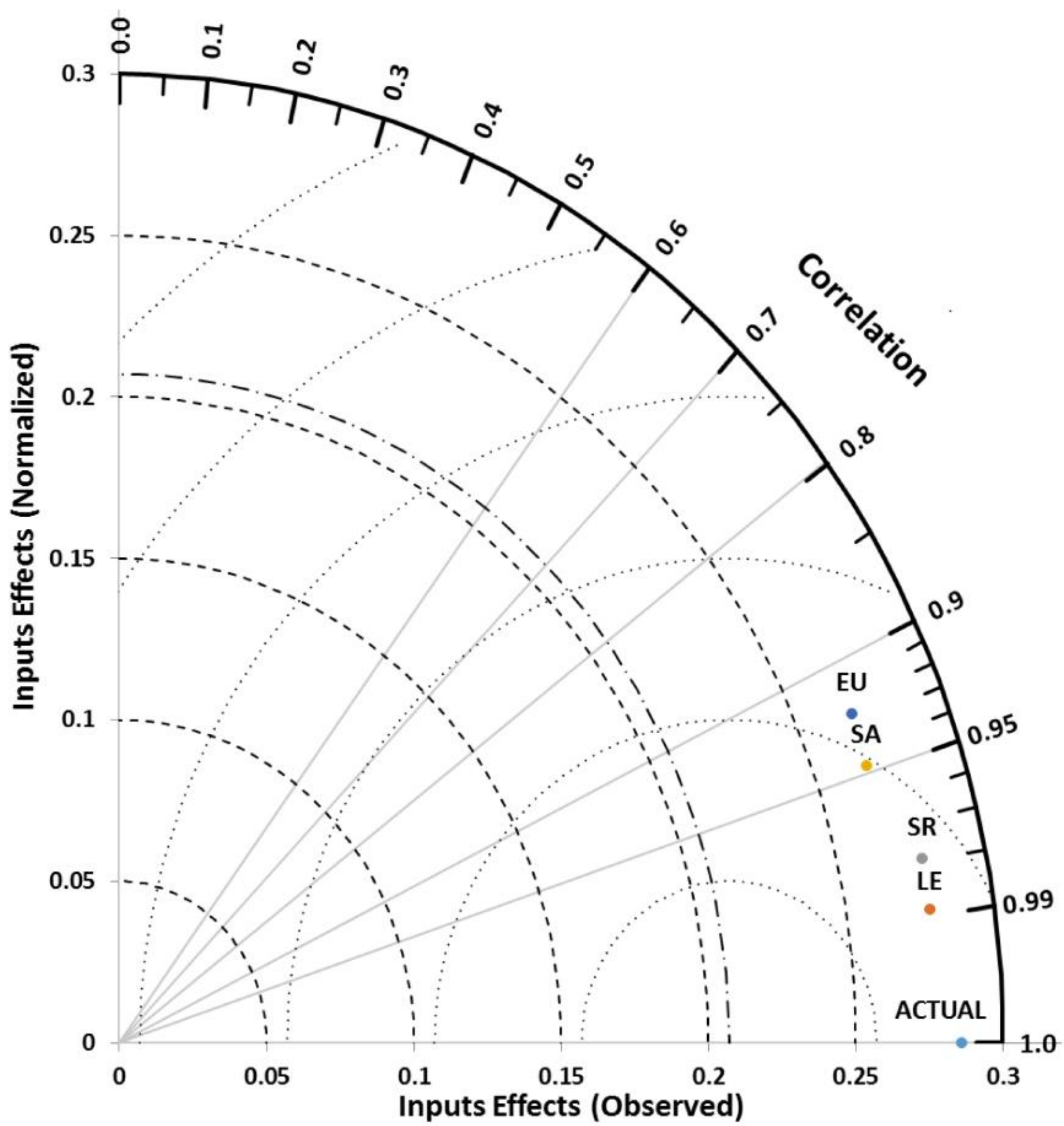

Figure 4: Inputs ranking results using Taylor graph.

5. Conclusion

The study utilized two different machine learning (ML) models (FFNN and ANFIS) to modelled and obtained predictions regarding the effects of the study choosing inputs i.e., learners' encouragement (LE), students' ratio (SR), systems availability (SA), and ease of usage (EU) on various internet learning technologies in the research area (Nigeria). All the research employed ML models predicted the effects of the research inputs with higher precision with NSE > 0.93 in the testing phase signifying a strong association between the inputs (LE, SR, SA, and EU) and the output variable i.e., internet-based learning.

Although, both models demonstrated good estimation ability. However, the ANFIS model surpasses the FFNN models as it has NSE > 0.96 compared to NSE > 0.93 for the FFNN model. Furthermore, the effects of each of the research inputs on the output were evaluated and determined using Taylor graph, and the results found learners' encouragement (LE), and students ration (SR) to be the most important factors affecting internet-based learning in Nigeria with correlation coefficient of > 0.98, while systems availability (SA) and ease of use (EU) have correlation coefficient of < 0.94 indicating a lesser association with the output. Though, the research developed two ML models and used Taylor graph to estimate the effects of LE, SR, SA, and EU on internet-based learning technologies and ranked the relative effect of each of the inputs respectively. Both approaches have proven to be robust and precise, but the study like any other study is limited dataset obtained in the research location i.e., Nigeria, and the techniques employed i.e., machine learning approach. Therefore, upcoming studies should combine both ML and classical approaches, and use more variables and other ML models such as "Multiple linear regression (MLR)" to investigate the factors affecting internet-based learning not only in developing nations like Nigeria but also in countries with advanced educational systems.

References

Alghamdi, S. R., & Bayaga, A. (2016). Use and attitude towards learning management systems (LMS) in Saudi Arabian universities. *Eurasia Journal of Mathematics, Science and Technology Education*, *12*(9), 2309-2330. https://doi.org/10.12973/eurasia.2016.1281a

Alhadreti, O. (2021). Assessing academics' perceptions of blackboard usability using SUS and CSUQ: A case study during the COVID-19 pandemic. *International Journal of Human–Computer Interaction*, *37*(11), 1003-1015. https://doi.org/10.1080/10447318.2020.1861766

Aryani, I. G. A. I., Saientisna, M. D., & Citrawati, N. P. E. W. (2022). Meaning Search of Agricultural Technology Terms Internet Based-Learning in Translation and Learning English. *Basic and Applied Education Research Journal*, *3*(2), 85-97. https://doi.org/10.1002/itl2.418

Bailey, D. R., Almusharraf, N., & Almusharraf, A. (2022). Video conferencing in the e-learning context: explaining learning outcome with the technology acceptance model. *Education and Information Technologies*, *27*(6), 7679-7698. https://doi.org/10.1007/s10639-022-10949-1

Cavus, N., Mohammed, Y. B., & Yakubu, M. N. (2021a). An artificial intelligence-based model for prediction of parameters affecting sustainable growth of mobile banking apps. *Sustainability*, *13*(11), 6206. https://doi.org/10.3390/su13116206

Cavus, N., Mohammed, Y. B., & Yakubu, M. N. (2021b). Determinants of learning management systems during COVID-19 pandemic for sustainable education. *Sustainability*, *13*(9), 5189. https://doi.org/10.3390/su13095189

Chen, W., Sanderson, N. C., Nichshyk, A., Bong, W. K., & Kessel, S. (2021). Usability of Learning Management Systems for Instructors–The Case of Canvas. *In Learning and Collaboration Technologies: New Challenges and Learning Experiences: 8th International Conference, LCT 2021, Held as Part of the 23rd HCI International Conference, HCII 2021, Virtual Event, July 24–29, 2021, Proceedings, Part I* (pp. 210-223).https://doi.org/10.1007/978-3-030-77889-7_14

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, *35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: a ten-year update. *Journal of management information systems*, *19*(4), 9-30. https://doi.org/10.1080/07421222.2003.11045748

Fathema, N., Shannon, D., & Ross, M. (2015). Expanding the Technology Acceptance Model (TAM) to examine faculty use of Learning Management Systems (LMS) in higher education institutions. *Journal of Online Learning & Teaching*, *11*(2). https://doi.org/10.1109/siie.2015.7451676

Funda, V., & Jali, L. (2022). Effects of emergency remote teaching on academic performance of undergraduate students during COVID-19 pandemic in South Africa. In *International Conference on Emerging Technology and Interdisciplinary Sciences* (pp. 82-88). https://doi.org/10.3390/educsci12110771

Gomersall, S., & Floyd, A. (2022). Resilience: Myanmar students' experiences of overcoming eLearning challenges during COVID 19 and political instability. *Asia Pacific Education Review*, 1-13. https://doi.org/10.1007/s12564-022-09781-6

Gunawan, G., Sahidu, H., Susilawati, S., Harjono, A., & Herayanti, L. (2019). Learning management system with Moodle to enhance creativity of candidate physics teacher. *In Journal of Physics: Conference Series*(Vol. 1417, No. 1, p. 012078). IOP Publishing.https://doi.org/10.1088/1742-6596/1417/1/012078

Hussain, S. A., Cavus, N., & Sekeroglu, B. (2021). Hybrid machine learning model for body fat percentage prediction based on support vector regression and emotional artificial neural networks. *Applied Sciences*, *11*(21), 9797. https://doi.org/10.3390/app11219797

Liao, C., Chen, J.-L., & Yen, D. C. (2007). Theory of planning behavior (TPB) and customer satisfaction in the continued use of e-service: An integrated model. *Computers in human behavior*, *23*(6), 2804-2822. https://doi.org/10.1016/j.chb.2006.05.006

Mahfoodh, H., &AlAtawi, H. (2020, December). Sustaining higher education through elearning in post Covid-19. In *2020 Sixth International Conference on e-learning (econf)* (pp. 361-365). IEEE.https://doi.org/10.1109/econf51404.2020.9385477

Moazenzadeh, R., Mohammadi, B., Shamshirband, S., & Chau, K.-w. (2018). Coupling a firefly algorithm with support vector regression to predict evaporation in northern Iran. *Engineering Applications of Computational Fluid Mechanics, 12*(1), 584-597. https://doi.org/10.1080/19942060.2018.1482476

Mohammadi, M. K., Mohibbi, A. A., & Hedayati, M. H. (2021). Investigating the challenges and factors influencing the use of the learning management system during the Covid-19 pandemic in Afghanistan. *Education and Information Technologies, 26*, 5165-5198. https://doi.org/10.1007/s10639-021-10517-z

Mohammed, Y. B., & Karagozlu, D. (2021). A Review of Human-Computer Interaction Design Approaches towards Information Systems Development. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience, 12*(1), 229-250. https://doi.org/10.18662/brain/12.1/180

Nizar, M. (2020). Factors affecting the effectiveness of accounting information systems in public listed companies in Sri Lanka. International Journal of Advanced Multidisciplinary Research, 7(9), 1-6.https://doi.org/10.31357/fmscmst.2008.00215

Nourani, V., Elkiran, G., & Abdullahi, J. (2020). Multi-step ahead modeling of reference evapotranspiration using a multi-model approach. *Journal of Hydrology, 581*, 124434. https://doi.org/10.1016/j.jhydrol.2019.124434

Rani, M., Srivastava, K. V., & Vyas, O. P. (2016). An ontological learning management system. *Computer Applications in Engineering Education, 24*(5), 706-722. https://doi.org/10.1002/cae.21742

Sharifov, M., Safikhanova, S., & Mustafa, A. (2021). Review of Prevailing Trends Barriers and Future Perspectives of Learning Management Systems (LMSs) in Higher Education Institutions. *International Journal of Education and Development using Information and Communication Technology, 17*(3), 207-216. https://doi.org/10.4018/978-1-4666-4590-5.ch009

Thanh, H. V., Binh, D. V., Kantoush, S. A., Nourani, V., Saber, M., Lee, K. K., & Sumi, T. (2022). Reconstructing daily discharge in a megadelta using machine learning techniques. *Water Resources Research, 58*(5), e2021WR031048. https://doi.org/10.1029/2021wr031048

Tikhamarine, Y., Malik, A., Kumar, A., Souag-Gamane, D., & Kisi, O. (2019). Estimation of monthly reference evapotranspiration using novel hybrid machine learning approaches. *Hydrological sciences journal, 64*(15), 1824-1842. https://doi.org/10.1080/02626667.2019.1678750

Tsimba, G., Mugoniwa, B., &Mutembedza, A. N. (2022, May). Equitable Access to eLearning during Covid-19 Pandemic and beyond. A Comparative Analysis between Rural and Urban Schools in Zimbabwe. In *2022 IST-Africa Conference (IST-Africa)* (pp. 1-8). IEEE.https://doi.org/10.23919/ist-africa56635.2022.9845566

Umar, I. K., Gökçekuş, H., & Nourani, V. (2022). An intelligent soft computing technique for prediction of vehicular traffic noise. *Arabian Journal of Geosciences, 15*(19), 1571.

Yakubu, M., Hassan, A., Ahmad, A., Musa, K., & Gital, A. (2018). Mobile learning stimulus in Nigeria. *Global Journal of Information Technology: Emerging Technologies, 8*(3), 95-101. https://doi.org/10.1007/s12517-022-10858-0

Yakubu, M. N., Dasuki, S. I., Abubakar, A. M., & Kah, M. M. (2020). Determinants of learning management systems adoption in Nigeria: A hybrid SEM and artificial neural network approach. *Education and Information Technologies*, *25*, 3515-3539. https://doi.org/10.1007/s10639-020-10110-w

Access this Article in Online	
	Website: www.ijarm.com
Quick Response Code	Subject: Education
DOI:10.22192/ijamr.2023.10.05.005	

How to cite this article:
Yakubu Bala Mohammed, Mohammed Bula. (2023). A Machine Learning Model for Prediction of Factors Affecting Internet-Based Learning Technologies. Int. J. Adv. Multidiscip. Res. 10(5): 40-51.
DOI: http://dx.doi.org/10.22192/ijamr.2023.10.05.005