IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 5, October 2025, pp. 3647~3655
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i5.pp3647-3655

A competitive learning approach to enhancing teacher effectiveness and student outcomes

Ilyas Tammouch[1], Soumaya Nouna[2], Abdelamine Elouafi[1], Assia Nouna[2]
[1]Laboratory of Telecommunications Systems and Decision Engineering, Faculty of Science, Ibn Tofail University, Kenitra, Morocco
[2]Laboratory LAMSAD, Department of Mathematics and Informatics, Hassan First University of Settat, Berrechid, Morocco

Article Info

Article history:

Received Nov 27, 2024
Revised Jul 26, 2025
Accepted Aug 06, 2025

Keywords:

Clustering
Competitive learning
Education reform
Machine learning
Teacher competence

ABSTRACT

Machine learning has found extensive application and improvement in the field of education. Nevertheless, there remains a lack of research studies focusing on unsupervised learning within this domain. To address this gap, our study aims to investigate the relationship between teacher attributes and student achievement in Morocco while identifying regions requiring attention and intervention, using a novel clustering approach based on unsupervised competitive learning, specifically the 'Centroid neural network', to cluster Moroccan teachers based on their qualities and qualifications. Teacher qualities and qualifications are operationalized as initial teaching qualifications, completion of training programs, and employment status. To achieve our objective, we utilize the program for international student assessment (PISA) dataset, which provides comprehensive responses from individual students, including information on parental backgrounds, socio-economic positions, and school conditions. Additionally, we incorporate data from the teacher questionnaire, which encompasses background information, initial education, professional development, teaching practice, and teacher beliefs and attitudes. Consistent with previous research, our findings suggest that teachers' qualities and qualifications significantly influence student performance. Furthermore, our clustering approach identifies regions where there is a pronounced prevalence of attributes negatively impacting student achievement. Urging academicians to incorporate resilience-building measures into the design of policies in these regions to improve students' educational outcomes.

Corresponding Author:

Ilyas Tammouch
Laboratory of Telecommunications Systems and Decision Engineering, Faculty of Science
Ibn Tofail University
Kenitra-14000, Morocco
Email: ilyas.tammouch@uit.ac.ma

1. INTRODUCTION

Several empirical studies concentrating on teacher quality have focused on student achievement as a focal point. Students' abilities acquired throughout their academic experience are vital for their success in the labor market, and understanding which style of teacher is more likely to favorably effect their human capital accumulation process is critical in any endeavor to boost their performance. Policymakers, educational institutions, parents, and other education stakeholders are all involved these days. Many studies are being conducted to identify the determining factors influencing student success in order to improve student achievement. All of them share the same findings, showing a strong correlation between instructor characteristics and student performance. The factors that the researcher pays close attention to in regard to teacher characteristics are education background, experience, certificate status, leadership experience, perseverance, teacher evaluation score, and preparedness for class work [1]–[7], [8]–[16].

Chetty *et al.* [17] found that students instructed by highly effective teachers, as indicated by student growth percentiles (SGPs) and value-added measures (VAMs), exhibited a greater likelihood of attending college, achieving higher earnings, living in affluent communities, accumulating retirement savings, and having fewer children during their teenage years. In a similar context, Bettinger and Long [18] examined a substantial sample of public institutions in Ohio and discovered that adjunct faculty increased the likelihood of student attrition during the second year. Their research examined the impact of adjunct instructors on enrollment and success rates in subsequent courses, indicating that adjuncts and graduate assistant instructors diminish subsequent interest in a subject more than full-time, tenure-track faculty, although the effect is minimal and varies significantly across disciplines. Hoffmann and Oreopoulos [5] demonstrate that, although students' perceptions of their instructors' teaching effectiveness serve as a valid assessment of teachers' impact on student performance, objective criteria seem to be irrelevant. Our research enhances existing literature by demonstrating the influence of instructors' teaching experience and prior training on Moroccan students' performance in the program for international student assessment (PISA) test, while also identifying areas requiring attention and intervention. We assess students' performance by calculating the average of plausible values derived from examinations on a certain subject. These metrics of student performance allow us to assess the impact of teachers' attributes and credentials on student success. The document is structured as follows: section 2 delineates data regarding student and teacher attributes and the methodology employed in the study; section 3 articulates the findings; and section 4 provides a conclusion.

2. DATA AND METHODS

2.1. Data

The PISA assesses 15-year-old students' ability to apply their reading, mathematics, and science knowledge and abilities to real-world problems [19], [20]. We chose PISA since it is one of the only open-source empirical data sets on Moroccan students' academic attainment. Second, PISA gathers specific information about each student, such as their parents' backgrounds, financial condition, school environment, class size, and so on. We can investigate the relationship between educational performance and the factors that impact it because of the breadth of the PISA dataset. Finally, unlike previous years, PISA 2018 participants were requested to complete a questionnaire regarding their educational perspectives as well as their emotional health.

This study utilizes two distinct datasets: the PISA 2018 student survey data covering 6814 Moroccan students and a corresponding teacher questionnaire dataset. The linkage between these datasets is established using the shared identifier column "CNTSCHID (Intl. School ID)." Through this linkage, a merged dataframe is generated. The combined dataframe integrates the mean plausible values for mathematics, science, and reading for all the individual students. It also has pertinent information on the qualifications and attributes of their teacher, such as queries on "What were the sources of your initial teaching certification?", "What is your current work status as a teacher?", and "Did you receive a teacher education or training program?" Together, this dataset is the basis of the examination of the relationship between student achievement and teacher attributes. Given the unequal distribution of teachers in the various regions of Morocco, we used a representative random sampling method whereby 65 teachers from each respective region were chosen. This sampling technique enabled the achievement of results closely aligned with the population mean and hence made possible meaningful comparison between the regions. For researchers who would want to use the Moroccan PISA dataset for their own analyses, access to the data is granted via the official OECD website's Morocco individual page at https://www.oecd.org/pisa/data/2018database/. The site offers a user-friendly interface for accessing the dataset files while providing a view of the dataset structure and variables.

2.2. Studying the impact of teacher's qualities on students' assessment

The initial stage of our study is to carry out a preliminary analysis to examine the effect of teacher characteristics on pupil achievement, with the PISA data set. In analyzing the data, we employed one-way analysis of variance (ANOVA), a common statistical technique for assessing variances among two independent populations that fulfill the criteria of normal distribution and equality of variance. ANOVA is particularly useful in the analysis of variation in a continuous response variable under conditions defined by discrete factors, i.e., classification variables with nominal levels. ANOVA is frequently utilized in testing the equality of various means by comparing group variation and within-group variance. Widespread availability of ANOVA in statistical software packages ensures that researchers from various fields can utilize this analytical tool [21].

We employed a one-way ANOVA in the present study to evaluate the main effects and interaction effects of categorical variables, specifically teacher qualifications and qualities, on a continuous dependent variable, i.e., student evaluation. We considered the level of significance at $p<0.05$, therefore referring to results below this level as statistically significant. In order to better visualize the correlation between the characteristics of educators and ratings by students, we additionally used box plots as graphical portrayals of the distribution of data and which assist in finding patterns or outliers.

2.3. Clustering teachers (centroid neural network algorithm)

Unsupervised learning is a subset of machine learning that deals with the analysis of data without any explicit labels or target values, in the hope of identifying underlying patterns, structures, or relationships contained within the data itself [22]. Clustering, a fundamental technique under unsupervised learning, is a popular method applied across scientific, technological, and commercial fields to analyze multivariate data. The process entails the division of data into significant groups or clusters derived according to inherent similarities or differences [23]. There has been a large body of work on clustering techniques, and as a result, numerous algorithms have been proposed that utilize different approaches to enhancing efficient data categorization [24]. Clustering algorithms in unsupervised learning utilize epochs and weights. An epoch means a single pass or iteration over the whole dataset while training, in which the algorithm sequentially updates data points' or clusters' weights with the aim of enhancing the clustering outcome. The weights are the relevance or importance of every data point for clustering. By adjusting weights at every epoch, clustering algorithms attempt to minimize a specified objective function, e.g., within-cluster distance or between-cluster distance. The iterative procedure is repeated until convergence, i.e., the algorithm stabilizes and the clustering solution does not change significantly.

The use of clustering algorithms, along with their management of epochs and weights, enables researchers and practitioners to extract hidden patterns, develop insights, and aid decision-making in numerous areas such as data mining, pattern recognition, image processing, market segmentation, and many others. Deep learning techniques have also shown promise in handling high-dimensional mathematical systems, demonstrating the growing versatility of neural models in solving complex problems [25]. Among a number of clustering algorithms, the centroid neural network (CentNN) is an unsupervised competitive learning algorithm based on the conventional k-means clustering algorithm introduced by Park [26]. In every pass, the CentNN computes the cluster centroids of the input data vectors. When an input data point, x, is presented to the network, the neuron that demonstrates the minimum distance to x is selected as the winner neuron at epoch (k).

The neuron identified as the victor during epoch (k-1) but designated as the loser in epoch (k) is termed the loser. The CentNN modifies its weights solely when the output neuron's status for the latest data diverges from its condition in the preceding epoch. Furthermore, the CentNN commences with two initial clusters and incrementally augments the number of clusters to attain the optimal clustering outcome. In comparison with conventional clustering techniques such as self-organizing maps (SOM) [27]–[29] or k-means [24], [30], the CentNN approach has a number of benefits in unsupervised competitive learning. Although SOMs also apply a neural network structure to form a neuron grid and adapt weights to properly map input data topologically, they may suffer from the influence of initial learning rates and may potentially converge to poor solutions [31]. Conversely, the k-means algorithm is a more straightforward approach that assigns data to a predetermined number of clusters depending on the provided centroids. Nevertheless, it can be influenced by the choice of initial centroids [32]. In contrast, CentNN does not rely on predetermined learning gain schedules or fixed repetitions, providing greater flexibility and demonstrating superior performance in various experiments.

In our study, we first estimated the appropriate number of clusters necessary for effective data clustering. Subsequently, we utilized the CentNN algorithm to group teachers into clusters based on their qualifications, which impact student assessment. Cluster 0 represents teachers with qualities that negatively affect student achievement, while cluster 1 comprises teachers who positively contribute to student performance.

2.4. Regions' teachers' qualities level

After clustering teachers into n clusters (assuming n=2 based on the elbow graph plot), we sorted the clustered data by area, then calculated the number of instructors assigned to cluster 0 and the number of teachers assigned to cluster 1 for each region. Afterwards, we calculated the difference between the two counts and then scaled it to fall within the range of -1 to 1, relative to the differences in counts seen in other regions. For this purpose, we propose D as "the difference level between teachers assigned to cluster 1 compared to teachers assigned to cluster 0". It is calculated according to the following formula:

$$D = \frac{c1-c0}{\left\lceil\frac{c1+c0}{2}\right\rceil} \quad (1)$$

Where C1 is number of teachers assigned to cluster 1 and C0 is number of teachers assigned to cluster 0. A negative value of the scaled D value indicates that the region in question has a high number of teachers whose qualities negatively impact student assessment. Most teachers in this region were assigned to cluster 0.

3. RESULTS AND DISCUSSION

3.1. Studying the impact of teacher's qualities on students' assessment

Table 1 presents the results, demonstrating a significant association between teacher qualities and student performance. The ANOVA test conducted revealed a statistically significant relationship (p-value less than the significance level of 0.05) between the independent variable, teacher qualities and qualifications, and the dependent variable, students' performance in the PISA test of 2018. This finding suggests that factors such as initial teaching qualifications, employment status, and completion of a teacher training program have an impact on students' achievement in the PISA test. Moreover, the F-value obtained from the ANOVA test confirms a strong relationship between the independent variable (teacher quality) and the dependent variable (student achievement in the PISA test of 2018). In other words, it indicates that the variation observed between the sample means is significantly higher than the variation within the samples, providing evidence to reject the null hypothesis.

Table 1. One-way ANOVA results on teacher qualities and student performance

Teacher qualities	F score	p-value
Initial teaching qualifications	225.22	1.10e-145
Employment status	159.58	3.18e-103
Completion of a teacher education or training program	248.11	3.01e-108

According to the findings in Figure 1, we can see that the completion of a teacher education or training program lasting longer than 1 year has a substantial impact on academic progress. Furthermore, students who are taught by teachers with initial teaching qualifications from an eligible educational institute demonstrate higher levels of cognitive skills. Respectively, it can be inferred that employment status has a beneficial impact on student academic ability.

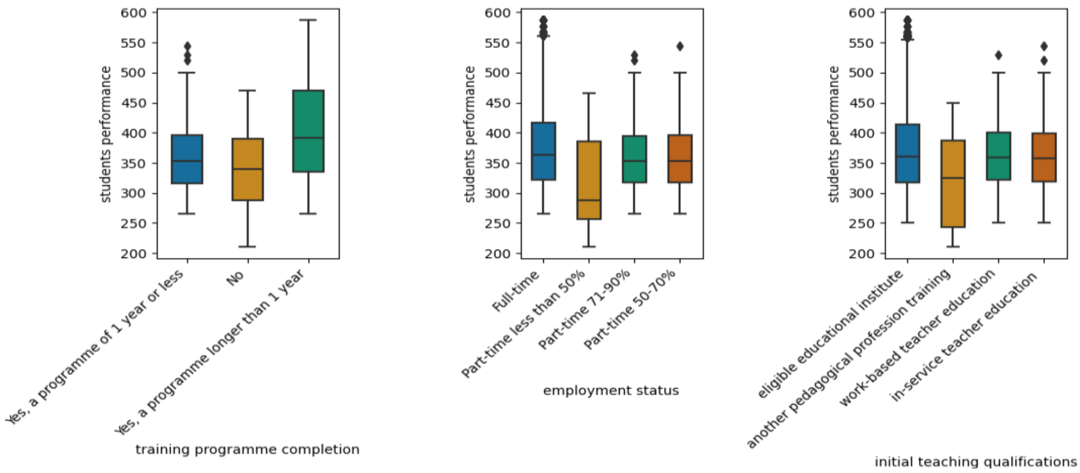

Figure 1. Boxplots displaying relationship between students' performance and teacher's qualities

3.2. Clustering

3.2.1. Data preprocessing

Following data normalization, we applied principal component analysis (PCA) to reduce the dimensionality of the dataset while preserving significant variance. We selected principal components (PCs) with a cumulative explained variance ratio exceeding 0.90 to ensure that the reduced dataset retained most of the original information. Based on this criterion, we chose two PCs from the normalized data, which effectively captured the key patterns relevant to the CentNN's performance in evaluating teacher effectiveness.

3.2.2. Estimating the number of clusters

After charting the curve as shown in Figure 2, we selected 2 as the cut-off point. Although the within-cluster sum of squares (WCSS) is still decreasing, it doesn't seem to be doing so at a big enough rate. Therefore, adding more clusters is not justified by the added complexity.

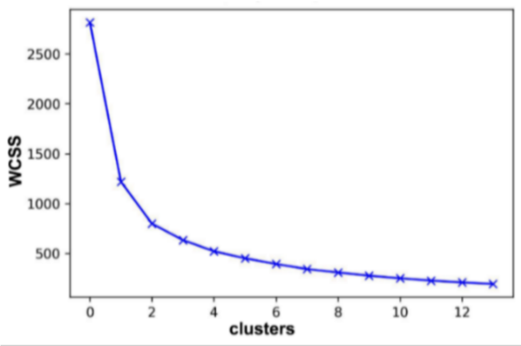

Figure 2. Estimating number of clusters using elbow method

3.2.3. Clustering teachers

After estimating the number of clusters to be used in this investigation. The two PCs are then fed into the CentNN, allowing us to group teachers into groups based on their qualities factors that influence academic achievement. We want to identify teachers who have characteristics that have a detrimental impact on student progress and bring them together to establish strategies for further educational reform. According to the bar chart displayed in Figure 3, which compares the two clusters-the number of students assigned to each cluster and the "student performance" metric derived from the mean plausible values for math, science, and reading, sourced from the initial integrated dataset-it can be seen that teachers with qualities that have a negative impact on student achievement lie in cluster 0, whereas cluster 1 describes teachers who have positive effects on student achievement.

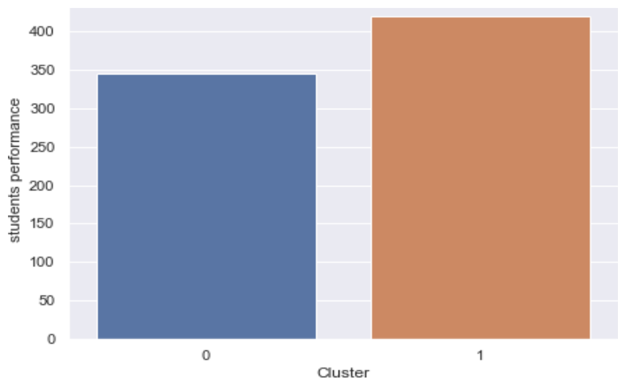

Figure 3. Bar chart of clustering data using CentNN

3.3. Evaluation and comparison of three algorithms

Table 2 presents the results of a comparative analysis of three algorithms, evaluated based on multiple performance metrics. The study examined the impact of these algorithms on clustering teachers by calculating the silhouette coefficient (SC), Calinski-Harabasz index (CHI), and Davies-Bouldin index (DBI). The findings indicate that the CentNN outperformed both the SOM and k-means algorithms, as evidenced by higher SC, CHI, and DBI values. This suggests that the CentNN is more effective in grouping teachers with comparable attributes and qualifications.

Table 2. Analysis and comparison of three clustering algorithms using SC, CHI, and DBI

Algorithm	SC	CHI	DBI
k-means	0.51	68138.47	0.97
CentNN	0.53	68615.31	0.95
SOM	0.50	65221.55	1.14

3.4. Regions' teachers' qualities level

To assess and compare the quality levels of teachers across different regions, the following steps are conducted: i) step 1 for each region, we quantify the number of teachers assigned to cluster 0 and cluster 1, as illustrated in Table 3 and ii) step 2 using the (1), we calculate D as "the difference level between the teachers assigned to cluster 1 compared to teachers assigned to cluster 0".

The findings presented in Table 4 provide a window into the complex framework that is the educational landscape across different regions. Notably, they offer valuable insights into the distribution of teachers whose qualities significantly influence students' assessments. This highlights the critical role of educators in shaping the educational outcomes of young minds.

Table 3. Number of teachers assigned to cluster 0 and teachers assigned to cluster 1

Region	Number of teachers assigned to (cluster 0)	Number of teachers assigned to (cluster 1)
Tanger-Tetouan-Al Hoceima	31	34
Oriental	33	32
Fès-Meknès	31	34
Rabat-Salé-Kénitra	25	40
Béni Mellal-Khénifra	43	22
Casablanca-Settat	18	47
Marrakech-Safi	39	26
Drâa-Tafilalet	30	35
Souss-Massa	31	34
Guelmim-Oued Noun	34	31
Laayoune-Sakia El Hamra	22	43
Eddakhla-Oued Eddahab	44	21

Table 4. difference between the number of teachers in each cluster

Region	D
Tanger-Tetouan-Al Hoceima	0.09
Oriental	-0.03
Fès-Meknès	0.09
Rabat-Salé-Kénitra	0.46
Béni Mellal-Khénifra	-0.64
Casablanca-Settat	0.89
Marrakech-Safi	-0.40
Drâa-Tafilalet	0.15
Souss-Massa	0.09
Guelmim-Oued Noun	-0.09
Laayoune-Sakia El Hamra	0.64
Eddakhla-Oued Eddahab	-0.70

Examining the regional variations reveals a considerable variation in the distribution of teachers who possess both positive and negative effects on students' ratings. 'Casablanca-Settat' is one of the regions that stands out clearly with a high rate of teachers who possess characteristics which exert positive effects on their students' academic development. This finding highlights the possibility of reproducing and expanding the strategies employed by these teachers in order to improve the general standard of education across different areas. On the other hand, having a larger number of teachers with potentially negative traits in regions such as 'Eddakhla-Oued Eddahab' and 'Béni Mellal-Khénifra' raises alarm regarding its effect on students' achievement. These findings require a comprehensive exploration of the variables that contribute to this situation, thus prompting educational stakeholders to develop targeted interventions and support systems for teachers in these fields with a view to enriching their pedagogical practices and effectiveness. However, as we unpack these findings further, it is crucial to note that regional disparities are only part of the complex education picture. Even areas that exhibit relatively small differences, maybe towards a value of close to zero, ought not to be dismissed in forward thinking for education reforms. Despite their apparently small differences, these regions could have hidden potential or particular contextual issues that will be useful to inform the overall development of the educational system.

Harnessing this untapped potential in a sound way require policymakers and stakeholders interested in education need to have an overarching and holistic approach to education reform. Instead of following a blanket policy, an attempt should be made to decipher the peculiarities and the environment of every place. In this way, region-specific interventions can be made that cater to the specific requirements and challenges of the students and teachers in various areas. A comprehensive strategy not only makes certain that everything is addressed but also guarantees a feeling of ownership and empowerment by the local communities. When teachers, parents, and pupils become active stakeholders in the direction of their learning experience, a ripple effect of constructive change infiltrates the whole jurisdiction, resulting in a fairer and more efficient educational system.

Overall, the results presented in Table 4 not only illuminate the disparities in teacher quality across regions but also as an impetus for taking an integrated and comprehensive approach to education reform. Embracing the diversity of our educational system and leveraging the strengths of each region will undoubtedly propel us towards a future where every student receives a high-quality education, irrespective of where they live. Such a future is not only aspirational but a fundamental right that will foster a generation of empowered individuals, ready to tackle the challenges of tomorrow and contribute to the progress of society as a whole.

4. CONCLUSION

Schools need to identify which elements are more likely to influence student success in order to provide better instruction. However, limited research has explored the specific teacher attributes that significantly contribute to students' academic growth, particularly in the context of Moroccan students. This study investigates the influence of teacher qualities and qualifications on student performance using the PISA dataset. Additionally, clustering teachers based on their attributes that impact student outcomes is essential for identifying regions requiring targeted interventions. The results reveal a significant correlation between the independent variables (teacher qualities and qualifications) and the dependent variable (student performance). It was discovered that teachers who completed a teacher education or training program longer than 1 year as well as teachers who got their initial teaching qualifications at an educational institute eligible to educate or train teachers seemed to produce a statistically significant effect on students' performance. This positive effect on students' assessments implies that recent trends toward hiring young, Inexperienced teachers are found to potentially have a detrimental effect on student performance. Additionally, through the clustering approach, it was observed that the region of "Eddakhla-Oued Eddahab" and 'Béni Mellal-Khénifra' has the highest concentration of teachers whose qualities negatively impact student achievement. This finding emphasizes the importance of academic institutions incorporating resilience-building strategies into policy design for these specific regions.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ilyas Tammouch	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Soumaya Nouna		✓		✓		✓		✓	✓	✓	✓	✓		
Abdelamine Elouafi	✓		✓	✓			✓			✓	✓		✓	
Assia Nouna	✓		✓	✓			✓			✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest related to this work.

DATA AVAILABILITY

The data that support the findings of this study are openly available in the OECD PISA 2018 database at https://www.oecd.org/pisa/data/2018database/.

REFERENCES

[1] D. Card and A. B. Krueger, "Does school quality matter? returns to education and the characteristics of public schools in the United States," *Journal of Political Economy*, vol. 100, no. 1, pp. 1–40, 1992, doi: 10.1086/261805.

[2] S. Gerritsen, E. Plug, and D. Webbink, "Teacher quality and student achievement: evidence from a sample of Dutch twins," *Journal of Applied Econometrics*, vol. 32, no. 3, pp. 643–660, 2017, doi: 10.1002/jae.2539.

[3] P. Glewwe, E. Hanushek, S. Humpage, and R. Ravina, "School resources and educational outcomes in developing countries: a review of the literature from 1990 to 2010," in *Education Policy in Developing Countries*, 2011, pp. 13–64, doi: 10.3386/w17554.

[4] D. Goldhaber, "Everyone's doing it, but what does teacher testing tell us about teacher effectiveness?," *Journal of Human Resources*, vol. 42, no. 4, pp. 765–794, 2007, doi: 10.3368/jhr.xlii.4.765.

[5] F. Hoffmann and P. Oreopoulos, "Professor qualities and student achievement," *Review of Economics and Statistics*, vol. 91, no. 1, pp. 83–92, 2009, doi: 10.1162/rest.91.1.83.

[6] C. M. Hoxby and A. Leigh, "Pulled away or pushed out? explaining the decline of teacher aptitude in the United States," *American Economic Review*, vol. 94, no. 2, pp. 236–240, 2004, doi: 10.1257/0002828041302073.

[7] B. Jacob and L. Lefgren, "Principals as agents: subjective performance measurement in education," Cambridge, Massachusetts, 2005, doi: 10.3386/w11463.

[8] T. J. Kane, J. E. Rockoff, and D. O. Staiger, "What does certification tell us about teacher effectiveness? evidence from New York City," *Economics of Education Review*, vol. 27, no. 6, pp. 615–631, 2008, doi: 10.1016/j.econedurev.2007.05.005.

[9] S. G. Rivkin, E. A. Hanushek, and J. F. Kain, "Teachers, schools, and academic achievement," *Econometrica*, vol. 73, no. 2, pp. 417–458, 2005, doi: 10.1111/j.1468-0262.2005.00584.x.

[10] J. E. Rockoff, "The impact of individual teachers on student achievement: evidence from panel data," *American Economic Review*, vol. 94, no. 2, pp. 247–252, 2004, doi: 10.1257/0002828041302244.

[11] S. Sirait, "Does teacher quality affect student achievement? an empirical study in indonesia," *Journal of Education and Practice*, vol. 7, no. 27, pp. 34–41, 2016.

[12] L. M. Musau and M. J. Abere, "Teacher qualification and students academic performance in science mathematics and technology subjects in Kenya," *International Journal of Educational Administration and Policy Studies*, vol. 7, no. 3, pp. 83–89, 2015, doi: 10.5897/IJEAPS2014.0386.

[13] D. Mahler, J. Großschedl, and U. Harms, "Does motivation matter? – the relationship between teachers' self-efficacy and enthusiasm and students' performance," *PLoS ONE*, vol. 13, no. 11, 2018, doi: 10.1371/journal.pone.0207252.

[14] A. A. Khan *et al.*, "Instructional leadership and students academic performance: mediating effects of teacher's organizational commitment," *International Journal of Learning, Teaching and Educational Research*, vol. 19, no. 10, pp. 233–247, 2020, doi: 10.26803/IJLTER.19.10.13.

[15] M. Y. Taufan, "Professional development of teachers, competencies, educational facilities and infrastructure on teacher performance and learning achievement of high school students in Makassar City," *Golden Ratio of Social Science and Education*, vol. 2, no. 1, pp. 24–38, 2022, doi: 10.52970/grsse.v2i1.168.

[16] A. Elouafi, I. Tammouch, S. Eddarouich, and R. Touahni, "Uncovering key factors of student performance in math: an explainable deep learning approach using TIMSS 2019 data," *Information*, vol. 16, no. 6, 2025, doi: 10.3390/info16060480.

[17] R. Chetty, J. N. Friedman, and J. E. Rockoff, "Measuring the impacts of teachers II: teacher value-added and student outcomes in adulthood," *American Economic Review*, vol. 104, no. 9, pp. 2633–2679, 2014, doi: 10.1257/aer.104.9.2633.

[18] E. P. Bettinger and B. T. Long, "Do college instructors matter? the effects of adjuncts on students' interests and success," *NBER Working Papers Series*, 2004.

[19] G. Brunello and L. Rocco, "The effect of immigration on the school performance of natives: cross country evidence using PISA test scores," *Economics of Education Review*, vol. 32, no. 1, pp. 234–246, 2013, doi: 10.1016/j.econedurev.2012.10.006.

[20] P. Pholphirul and S. Teimtad, "Living with parents and educational outcomes in developing countries: empirical evidence from PISA Thailand," *Journal of Population Research*, vol. 35, no. 1, pp. 87–105, 2018, doi: 10.1007/s12546-017-9196-1.

[21] M. G. Larson, "Analysis of variance," *Circulation*, vol. 117, no. 1, pp. 115–121, Jan. 2008, doi: 10.1161/CIRCULATIONAHA.107.654335.

[22] C. M. Bishop, *Pattern recognition and machine learning*. Singapore: Springer, 2006.

[23] T. Hastie, J. Friedman, and R. Tibshirani, *The elements of statistical learning*. New York, United States: Springer, 2001, doi: 10.1007/978-0-387-21606-5.

[24] J. A. Hartigan and M. A. Wong, "Algorithm AS 136: a k-means clustering algorithm," *Journal of the Royal Statistical Society*, vol. 28, no. 1, pp. 100–108, 1979.

[25] S. Nouna, A. Nouna, M. Mansouri, I. Tammouch, and B. Achchab, "Two-dimensional Klein-Gordon and Sine-Gordon numerical solutions based on deep neural network," *IAES International Journal of Artificial Intelligence*, vol. 14, no. 2, pp. 1548–1560, 2025, doi: 10.11591/ijai.v14.i2.pp1548-1560.

[26] D. C. Park, "Centroid neural network for unsupervised competitive learning," *IEEE Transactions on Neural Networks*, vol. 11, no. 2, pp. 520–528, 2000, doi: 10.1109/72.839021.

[27] T. Kohonen, "The self-organizing map," *Proceedings of the IEEE*, vol. 78, no. 9, pp. 1464–1480, 1990, doi: 10.1109/5.58325.

[28] R. Wehrens and J. Kruisselbrink, "Flexible self-organizing maps in kohonen 3.0," *Journal of Statistical Software*, vol. 87, no. 7, 2018, doi: 10.18637/jss.v087.i07.

[29] G. Yen, "Self-organizing maps," in *Intelligent Systems*, Boca Raton, Florida: CRC Press, 2011, pp. 1–29.

[30] M. Ay, L. Özbakır, S. Kulluk, B. Gülmez, G. Öztürk, and S. Özer, "FC-Kmeans: fixed-centered K-means algorithm," *Expert Systems with Applications*, vol. 211, 2023, doi: 10.1016/j.eswa.2022.118656.

[31] A. Ultsch, “Kohonen’s self organizing feature map for exploratory data analysis,” *Proceedings INNC-90-PARIS*, vol. 1, pp. 305–308, 1990.
[32] L. M. Lecam and J. Neyman, *Proceedings of the fifth berkeley symposium on mathematical statistics and probability*. London, England: University of California Press, 1967.

BIOGRAPHIES OF AUTHORS

Dr. Ilyas Tammouch is a distinguished researcher at Ibn Tofail University, located in Kenitra, Morocco. His scientific interests are varied and cover areas such as machine learning, deep learning, data analysis, and evaluation systems. He can be contacted at email: ilyas.tammouch@uit.ac.ma.

Soumaya Nouna is a research scientist in the systems analysis and modelling and decision support research laboratory at Hassan First University, Settat. She holds expertise in mathematics, ML and DL. A Ph.D. researcher in mathematics and computer science, she has ample experience in her field. Her fields of interest are the analysis of differential equations, and ML algorithms. She is also believed to be the writer of several research papers and constantly strives to progress in her field. She can be contacted at email: s.nouna@uhp.ac.ma.

Abdelamine Elouafi is a Ph.D. candidate at Ibn Tofail University in Kenitra, Morocco, and a dedicated secondary school teacher. He holds a bachelor’s in computer engineering (2014) and a master’s in decision-making informatics (2019) from Sultan Moulay Slimane University, plus a teaching license from Fes (2016). Passionate about machine learning, deep learning, and data analysis. He can be contacted at email: abdelamine.elouafi@uit.ac.ma.

Assia Nouna is a researcher at the Systems Analysis and Modelling and Decision Support Research Laboratory at Hassan First University in Settat. A doctoral researcher in mathematics and computer science. She is currently working on deep learning and satellite imagery for agricultural applications. Her research aims to enhance agricultural practices through precise soil analysis, improving crop management, and yield predictions. Additionally, she has contributed to various projects and publications in the field, demonstrating her expertise in applying advanced computational techniques to solve real-world problems. She can be contacted at email: a.nouna@uhp.ac.ma.