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DATA-DRIVEN PROFILING OF ARABIC LANGUAGE PROFICIENCY: INTEGRATING FUZZY CLUSTERING AND NEURAL NETWORK ANALYSIS

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Abstract

Introduction: Evaluating multidimensional language competencies in tertiary-level Arabic education poses persistent methodological difficulties, as conventional scoring systems frequently reduce complex proficiency dimensions to single aggregated values that conceal underlying skill structures and diminish the instructional utility of assessment feedback. **Research Objectives:** The present study constructs an empirically grounded competency profiling framework by combining clustering algorithms with predictive modeling techniques to uncover latent proficiency patterns among Arabic language learners. **Methodology:** A cross-sectional quantitative design was adopted using data from 128 students in the Arabic Language Education program at Universitas Negeri Jakarta, whose scores across listening, speaking, reading, and writing skills were analyzed through Fuzzy C-Means (FCM) clustering to identify latent proficiency groupings, followed by the use of a feedforward neural network to model predictive relationships between individual skill domains and overall academic performance. **Results:** Three learner profiles emerged: low, moderate, and high proficiency each showing statistically significant inter-group differences across all skills ($p < 0.001$), with effect size estimates ($\eta^2 = 0.20–0.25$) confirming moderate to substantial cluster-level variance, while the neural network attained 93.33% accuracy with a minimal mean squared error (MSE = $2e^{-06}$). **Unique Contribution:** This study offers an empirically validated hybrid framework synthesizing exploratory clustering with predictive analytics to advance language competency assessment methodology. **Conclusion:** Arabic language proficiency appears to be organized along a clearly delineated continuum that is statistically distinguishable and reliably predictable. **Recommendations:** Future research should incorporate broader learner-level variables and apply this framework across diverse educational settings to strengthen generalizability and instructional relevance.

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Keywords: Arabic Language Assessment; Competency Profiling; Fuzzy C-Means Clustering; Neural Network; Educational Data Mining.

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Introduction

Arabic language proficiency assessment in higher education is inherently multidimensional, as learners' capabilities span the domains of listening, speaking, reading, and writing. These four skill areas serve as foundational indicators of linguistic mastery and are widely recognized as primary benchmarks for proficiency evaluation in both academic and professional contexts.[1] Nevertheless, development across these dimensions rarely progresses at a uniform rate, producing heterogeneous performance distributions among student populations.[2] Within numerous educational settings, traditional assessment practices frequently shaped by subjective judgment tend to compromise the objectivity and comprehensiveness with which learner competencies are measured.[3] This complex issue highlights the need for more systematic and data-oriented approaches to Arabic language assessment.

In recent years, educational data analysis techniques have provided alternative frameworks for identifying latent structures within performance data.[4] Clustering methods, particularly K-Means, have been widely employed to group individuals based on similarity patterns.[5] However, language competencies are rarely discrete or mutually exclusive. Students may demonstrate overlapping strengths across skills, making rigid classification insufficient for capturing authentic proficiency profiles. Fuzzy C-Means (FCM) clustering addresses this limitation by assigning degrees of membership to multiple clusters, thereby enabling a more flexible representation of competency structures.[6]

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[1] Mahyudin Ritonga et al., "Learning for Early Childhood Using the IcanDO Platform: Breakthroughs for Golden Age Education in Arabic Learning," *Education and Information Technologies* 28, no. 7 (2023): 9171–88, https://doi.org/10.1007/s10639-022-11575-7.

[2] Saleem Malik et al., "Enhancing Education Quality with Hybrid Clustering and Evolutionary Neural Networks in a Multi Phase Framework," *Scientific Reports* 15, no. 1 (2025): 21323, https://doi.org/10.1038/s41598-025-04622-z.

[3] Kiyan Sorgog and Masashi Kamo, "Quantifying the Precision of Ecological Risk: Conventional Assessment Factor Method vs. Species Sensitivity Distribution Method," *Ecotoxicology and Environmental Safety* 183 (November 2019): 109494, https://doi.org/10.1016/j.ecoenv.2019.109494; Torulf Palm, *Performance Assessment and Authentic Assessment: A Conceptual Analysis of the Literature*, n.d., https://doi.org/10.7275/0QPC-WS45; Tamara Kastorff et al., "Context-Specificity to Reduce Bias in Self-Assessments: Comparing Teachers' Scenario-Based Self-Assessment and Objective Assessment of Technological Knowledge," *Journal of Research on Technology in Education* 55, no. 6 (2023): 917–30, https://doi.org/10.1080/15391523.2022.2062498.

[4] Amani A. Aladeemy et al., "Advancements and Challenges in Arabic Sentiment Analysis: A Decade of Methodologies, Applications, and Resource Development," *Heliyon* 10, no. 21 (2024): e39786, https://doi.org/10.1016/j.heliyon.2024.e39786.

[5] Abiodun M. Ikotun et al., "K-Means Clustering Algorithms: A Comprehensive Review, Variants Analysis, and Advances in the Era of Big Data," *Information Sciences* 622 (April 2023): 178–210, https://doi.org/10.1016/j.ins.2022.11.139; Jelili Oyelade et al., "Data Clustering: Algorithms and Its Applications," *2019 19th International Conference on Computational Science and Its Applications (ICCSA)*, July 2019, 71–81, https://doi.org/10.1109/ICCSA.2019.000-1.

[6] Richard W. Grant et al., "Use of Latent Class Analysis and K-Means Clustering to Identify Complex Patient Profiles," *JAMA Network Open* 3, no. 12 (2020): e2029068, https://doi.org/10.1001/jamanetworkopen.2020.29068.

Beyond classification, understanding predictive relationships between language skills and overall academic achievement remains a complex issue. [7] Language acquisition involves interconnected cognitive and communicative processes that may not follow strictly linear patterns. In this context, predictive modeling techniques such as neural networks have been recognized for their capacity to capture nonlinear relationships among variables.[8] Within the broader development of artificial intelligence in education, such approaches offer the potential to support more evidence-based evaluation practices, although their application in Arabic language assessment remains relatively limited.[9]

Despite the growing body of research on machine learning in educational contexts, the integration of fuzzy clustering and predictive modeling for competency profiling in Arabic language assessment has not been extensively examined.[10] Prior studies have explored clustering algorithms, and neural network applications in educational prediction, yet empirical investigations combining these approaches to analyze multidimensional Arabic language competencies are still scarce. [11] Moreover, existing studies that have employed machine learning in Arabic language education have predominantly focused on automated scoring or text classification rather than on comprehensive learner profiling that encompasses all four core language skills. This gap indicates the need for a comprehensive framework that not only classifies proficiency patterns but also examines predictive relationships among skill indicators.

To address this need, the present study develops a data-driven competency profiling framework using Fuzzy C-Means clustering and neural network modeling. The study focuses on students enrolled in the Arabic Language Education program at Universitas Negeri Jakarta, representing a higher education context in which structured language assessment plays a central role in curriculum implementation. By examining performance data from standardized course assessments across four

[7] Mushtaq Hussain et al., "Using Machine Learning to Predict Student Difficulties from Learning Session Data," *Artificial Intelligence Review* 52, no. 1 (2019): 381–407, https://doi.org/10.1007/s10462-018-9620-8.

[8] Zhiwen Huang et al., "Tool Wear Predicting Based on Multi-Domain Feature Fusion by Deep Convolutional Neural Network in Milling Operations," *Journal of Intelligent Manufacturing* 31, no. 4 (2020): 953–66, https://doi.org/10.1007/s10845-019-01488-7.

[9] Yingyi Chen et al., "A Review of the Artificial Neural Network Models for Water Quality Prediction," *Applied Sciences* 10, no. 17 (2020): 5776, https://doi.org/10.3390/app10175776; Ali Çetinkaya and Ömer Kaan Baykan, "Prediction of Middle School Students' Programming Talent Using Artificial Neural Networks," *Engineering Science and Technology, an International Journal* 23, no. 6 (2020): 1301–7, https://doi.org/10.1016/j.jestch.2020.07.005.

[10] Fan Ouyang et al., "Integration of Artificial Intelligence Performance Prediction and Learning Analytics to Improve Student Learning in Online Engineering Course," *International Journal of Educational Technology in Higher Education* 20, no. 1 (2023): 4, https://doi.org/10.1186/s41239-022-00372-4.

[11] Kiran Kumar Reddy Yanamala, "Integrating Machine Learning and Human Feedback for Employee Performance Evaluation," *Journal of Advanced Computing Systems* 2, no. 1 (2024): 1–10, https://doi.org/10.69987/JACS.2022.20101; Iqbal H. Sarker, "Machine Learning: Algorithms, Real-World Applications and Research Directions," *SN Computer Science* 2, no. 3 (2021): 160, https://doi.org/10.1007/s42979-021-00592-x.

core skills, this research seeks to identify latent proficiency structures and analyze their relationship with overall academic achievement.

Through this integrated approach, the study aims to contribute to the advancement of objective and evidence-based Arabic language assessment practices. By combining fuzzy clustering for competency classification and neural network modeling for predictive analysis, this research provides an empirical framework for understanding multidimensional proficiency patterns. [12] The findings are expected to enrich the application of educational data mining in language evaluation and support more systematic competency profiling in higher education contexts.

Method

This study employed a quantitative cross-sectional design to examine data-driven competency profiling in Arabic language assessment.[13] The analysis focused on students' performance across four core language skills, namely listening, speaking, reading, and writing, using descriptive and analytical approaches to identify latent proficiency structures and examine their relationship with overall academic achievement.[14] The study aimed to classify students based on similarity patterns in multidimensional skill performance and to investigate predictive relationships among skill indicators.[15]

To achieve these objectives, the study integrated two complementary analytical techniques. First, Fuzzy C-Means (FCM) clustering was applied to group students according to their language skill scores, allowing for degrees of membership across clusters to represent overlapping competency profiles. [16] Second, a feedforward neural network model was developed to analyze predictive relationships between the four language skills and overall learning outcomes.[17] This sequential analytical framework enabled both classification and predictive modeling within a unified data-driven approach to Arabic language assessment.

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[12] Musa Adekunle Ayanwale et al., "Analyzing the Evolution of Machine Learning Integration in Educational Research: A Bibliometric Perspective," *Discover Education* 3, no. 1 (2024): 47, https://doi.org/10.1007/s44217-024-00119-5.

[13] Adawiya Taleb Shawaqfeh et al., "Data-Driven Language Assessment in Multilingual Educational Settings: Tools and Techniques for Proficiency Evaluation," *Migration Letters* 21, no. 2 (2024), https://migrationletters.com/index.php/ml/article/view/6215.

[14] Amirreza Mehrabi et al., "Enhancing Performance Factor Analysis through Skill Profile and Item Similarity Integration via an Attention Mechanism of Artificial Intelligence," *Frontiers in Education* 9 (November 2024): 1454319, https://doi.org/10.3389/feduc.2024.1454319.

[15] Turki Amira, "Implementing Digital Learning: Evaluating the Effect of Data-Driven Factors on Student Engagement and Performance in BAIS Courses," *Frontiers in Education* 11 (February 2026): 1727497, https://doi.org/10.3389/feduc.2026.1727497.

[16] Indah Purnama Sari et al., "Cluster Analysis Using K-Means Algorithm and Fuzzy C- Means Clustering For Grouping Students' Abilities In Online Learning Process," *Journal of Computer Science, Information Technology and Telecommunication Engineering* 2, no. 1 (2021), https://jurnal.umsu.ac.id/index.php/jcositte/article/view/6504.

[17] R. Jayasree and N. A. Sheela Selvakumari, "Analyzing Student Performance Using Fuzzy Possibilistic C-Means Clustering Algorithm," *Indian Journal Of Science And Technology* 16, no. 38 (2023): 3230–35, https://doi.org/10.17485/IJST/v16i38.226.

The participants of this study consisted of 128 students enrolled in the Arabic Language Education program at Universitas Negeri Jakarta, representing various academic levels within the higher education context. Participants were selected using purposive sampling based on the availability of complete academic assessment data covering four core language skills: listening, speaking, reading, and writing. Only students with complete and valid score records were included to ensure data consistency for subsequent analysis. The dataset comprised quantitative scores obtained from formal course evaluations conducted within the program, reflecting students' performance in each language skill across multiple semesters. The inclusion of students with varying proficiency levels provided sufficient variability in the data, enabling meaningful competency profiling and predictive modeling within a multidimensional assessment framework.

Data analysis was conducted using a sequential analytical framework integrating FCM clustering and neural network modeling. Before analysis, all variables were standardized using z-score normalization to ensure comparability across different score scales and to prevent variables with larger ranges from disproportionately influencing clustering results. In the first stage, FCM clustering was applied to the four language skill variables (listening, speaking, reading, and writing) to identify latent proficiency structures. The number of clusters was determined based on interpretability and cluster separation patterns, and the fuzzifier parameter (m) was set at 2, as commonly recommended in fuzzy clustering applications.[18] The algorithm was iteratively executed until convergence criteria were achieved, generating membership degrees for each student across clusters.

In the second stage, a feedforward neural network model was developed to examine predictive relationships between the four language skills and overall academic achievement. The dataset was divided into training and testing subsets using an 80:20 split—with 102 students in the training set and 26 in the testing set—to evaluate model generalization performance. The four language skills were used as input variables, and the overall achievement score was treated as the output variable. Model performance was evaluated using Mean Squared Error (MSE) and prediction accuracy by comparing predicted and actual values in the testing set. All analyses were conducted using R statistical software, and results were visualized through cluster distribution plots and prediction performance graphs to support interpretation.

Result and Discussion

The findings presented in this study emerge from the combined application of Fuzzy C-Means (FCM) clustering and neural network modeling, targeting four core Arabic language competencies: listening, speaking, reading, and writing. FCM clustering was utilized to group students according to similarities in their multidimensional skill profiles, with its degree-of-membership mechanism allowing overlapping competency structures to be captured more accurately than

[18] Yu Li et al., "Educational Data Mining for Students' Performance Based on Fuzzy C-means Clustering," *The Journal of Engineering* 2019, no. 11 (2019): 8245–50, https://doi.org/10.1049/joe.2019.0938.

conventional hard clustering approaches. A feedforward neural network was subsequently constructed to investigate predictive relationships between individual skill domains and overall academic achievement. Before clustering, all variables underwent z-score normalization to ensure cross-variable comparability and to prevent any single skill from exerting disproportionate influence over the grouping process. Collectively, these analytical procedures establish a structured, data-driven basis for profiling student competencies and examining their predictive patterns in Arabic language learning.

Regarding the dataset characteristics, the mean value of each scaled variable encompassing reading, writing, speaking, and listening reflects the general tendencies of the student population under examination. The standard deviation, in turn, captures the degree of dispersion within each variable, offering insight into the extent to which individual language skills contribute to differentiating student clusters. When normalization is properly applied, the clustering algorithm becomes better positioned to detect groups sharing genuinely similar characteristics, free from distortions introduced by discrepant measurement scales across variables.

Table 1. Data normalization

Attr (,"scaled : center")			
Reading	Writing	Speaking	Listening
82.56	85.50	84.62	83.90
Attr (,"scaled : scale")			
Reading	Writing	Speaking	Listening
12.3638050	9.6007015	8.0758900	8.8392677

Table 1 presents the normalization parameters applied to the four language skill variables. The mean (scaled center) represents the central value for each of the language skills measured: reading, writing, speaking, and listening. These mean values indicate that writing (85.50) and speaking (84.62) skills have slightly higher scores compared to reading (82.56) and listening (83.90). This difference in mean scores suggests that participants tend to perform better in writing and speaking compared to reading and listening. Although there is a slight difference, overall, the average scores for all language skills are relatively balanced, indicating that no skill is excessively dominant or significantly weaker among the participants.

The standard deviation of each scaled variable further illuminates the degree of score dispersion around the mean for each language skill. Reading demonstrates the highest variability, with a standard deviation of 12.36, surpassing those recorded for writing (9.60), listening (8.84), and speaking (8.08). This relatively wider spread in reading scores suggests greater inter-individual differences in participants' proficiency within that domain, pointing to a more heterogeneous distribution of capability among learnerss. Conversely, writing, speaking, and listening exhibit comparatively narrower dispersions, implying a higher degree of consistency in participant performance across these three skills. Understanding this variability is essential for interpreting the extent to which learners in the dataset diverge in their multidimensional Arabic language proficiency.

Fuzzy C-Means Clustering

To clarify the clustering outcomes, the mean scores of each language skill were calculated for every cluster identified through Fuzzy C-Means (FCM). Although FCM allows partial membership across clusters, dominant membership was used to interpret competency profiles for the purpose of profile characterization. The purpose of applying FCM was to reveal latent proficiency structures across listening, speaking, reading, and writing skills and to examine systematic differences among the identified groups.

Table 2. Mean Scores Across Clusters

Language Skills	Cluster 1 (Low)	Cluster 2 (Moderate)	Cluster 3 (High)
Reading	74.2	82.8	89.6
Writing	78.5	85.3	91.8
Speaking	76.1	87.4	90.9
Listening	75.4	86.2	89.7

The data presented in Table 2 reveal a discernible gradation of Arabic language proficiency across the three identified clusters. Cluster 1 consistently records the lowest mean scores across all four skill domains Reading (74.2), Writing (78.5), Speaking (76.1), and Listening (75.4) reflecting an overall low competency profile among students in this group. These learners appear to struggle with both receptive and productive skills, suggesting foundational difficulties in Arabic language acquisition that may require targeted instructional support across all domains. Cluster 2 represents an intermediate tier, with performance improvements evident across all skills, particularly in Speaking (87.4) and Listening (86.2), which appear comparatively stronger than Reading (82.8) and Writing (85.3), suggesting a relative oral proficiency advantage within this cluster. Cluster 3 demonstrates the highest and most balanced proficiency levels across all dimensions, with mean scores ranging from 89.6 to 91.8, indicative of advanced and stable linguistic mastery across both receptive and productive skills. Taken together, the systematic progression in mean values from Cluster 1 through Cluster 3 provides compelling evidence for the presence of structurally distinct competency profiles within the student dataset.

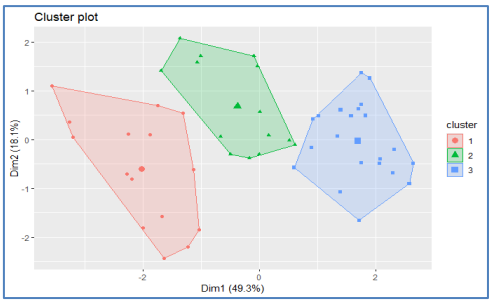


Figure 1. Clustering Results

Figure 1 illustrates the distribution of students across three clusters derived from the Fuzzy C-Means analysis, projected onto two principal dimensions. Dimension 1 (Dim1), which accounts for 49.3% of the total variance, appears to

represent the general proficiency gradient, clearly separating low-, moderate-, and high-competency groups along the horizontal axis. Cluster 1 (red) is positioned on the negative side of Dim1, indicating lower overall performance across the four language skills. Cluster 2 (green) occupies the central region, reflecting intermediate proficiency, while Cluster 3 (blue) is located on the positive side of Dim1, representing students with higher overall competency. The clear horizontal separation suggests that general language ability is the dominant factor structuring the clusters.

Dimension 2 (Dim2), explaining 18.1% of the variance, contributes additional differentiation within the competency structure, particularly distinguishing subtle variations among skill profiles in the moderate cluster and potentially capturing skill-specific strengths or weaknesses. The visual boundaries around each cluster indicate minimal overlap, suggesting a well-defined grouping pattern despite the fuzzy membership framework. Although Fuzzy C-Means allows partial membership across clusters, the spatial separation in the plot demonstrates that dominant memberships form distinct proficiency profiles. Overall, the two-dimensional projection confirms the presence of structured and interpretable competency groupings within the multidimensional Arabic language performance data.

Table 3. ANOVA Results Across Clusters

Language Skills	F-value	p-value	η^2 (Effect Size)
Reading	18.72	<0.001	0.23
Writing	21.34	<0.001	0.25
Speaking	15.89	<0.001	0.20
Listening	17.10	<0.001	0.22

The statistical results summarized in Table 3 confirm that meaningful differences exist among the three clusters across all four language skill domains. One-way ANOVA yielded significant F-values for Reading (F = 18.72), Writing (F = 21.34), Speaking (F = 15.89), and Listening (F = 17.10), with all corresponding p-values falling below the 0.001 threshold, thereby ruling out random variation as an explanation for the observed inter-cluster differences. Effect size estimates (η^2) ranging from 0.20 to 0.25 further indicate moderate to large practical significance, demonstrating that cluster membership accounts for a substantial portion of the variance in each skill domain. Among the four skills, Writing yields the strongest effect (η^2 = 0.25), followed by Reading (η^2 = 0.23), Listening (η^2 = 0.22), and Speaking (η^2 = 0.20). Collectively, these findings reinforce the construct validity of the derived competency groupings and substantiate the existence of structurally distinct proficiency profiles across the identified clusters.

Neural Network Analysis

Calculating the Mean Squared Error (MSE) constitutes a foundational step in evaluating model performance, as it provides an objective quantification of prediction error magnitude. As one of the most widely adopted metrics in regression-based analysis, MSE captures the average squared discrepancy between predicted and actual values, whereby smaller values correspond to greater predictive precision. Within the context of neural network modeling, MSE

computation is particularly indispensable for assessing how effectively the model has learned and internalized the input-output relationships present in the data. Without such a metric, determining whether the model has been adequately trained or still harbors substantial prediction errors would prove considerably difficult. MSE therefore functions as a critical diagnostic indicator throughout the model evaluation process, providing a reliable basis for subsequent refinements to the network architecture, training dataset, or optimization parameters as needed to enhance overall model performance. In the present study, MSE serves as the primary criterion for evaluating the neural network's effectiveness in predicting students' overall Arabic language skill outcomes, yielding important insights into predictive accuracy prior to advancing to more comprehensive analyses of model behavior.

The MSE obtained is 2e-06 (or 0.000002), indicating that the Neural Network model used in this study achieves a very low prediction error rate, signaling very high accuracy in predicting the language skills analyzed. This very small MSE suggests that the difference between predicted and actual values is almost undetectable, reflecting that the model has been well-trained and can model the relationship between inputs and outputs with high precision. With such a low MSE, it can be concluded that the model shows optimal performance, wherein the prediction errors are minimal and have little to no significant impact on the overall results.

The notably low MSE value further suggests that the model has successfully avoided overfitting, a condition in which a model becomes excessively adapted to training data and consequently loses its capacity to generalize to previously unseen observations. This consideration carries particular importance in educational data mining applications, as a model with robust generalization capability is better positioned to deliver reliable predictions beyond the training sample. Taken together, the exceptionally low MSE obtained in this study provides substantial evidence that the neural network model has attained a high level of predictive performance, characterized by minimal error and sufficient stability for practical deployment in language learning contexts. The model's accuracy across training iterations is illustrated in the plot below:

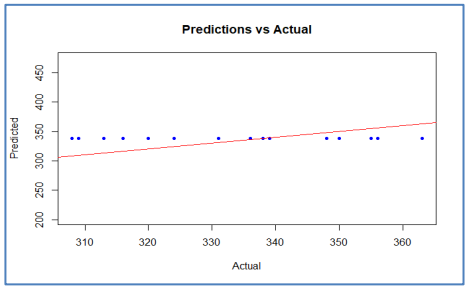


Figure 2. Plot Analysis of Neural Network

The Neural Network (NN) plot comparing predicted against actual values offers a clear visual depiction of the model's capacity to predict language skill outcomes accurately. Achieving an overall accuracy of 93.33%, the model demonstrates a strong alignment between its predictions and the observed values,

as reflected in the tight clustering of data points around the diagonal reference line that represents perfect prediction. This level of performance indicates that the neural network has generalized effectively across the tested skill domains, with the vast majority of predictions falling in proximity to their corresponding actual values.

A classification accuracy of 93.33% reflects the model's strong capability in predicting language skill outcomes, producing minimal discrepancies between predicted and actual values. This result demonstrates that the neural network has effectively captured the underlying input-output relationships and successfully reproduced the patterns inherent in the dataset. Nonetheless, the marginal deviations still discernible in the plot indicate that certain areas retain potential for further refinement. Overall, the attained accuracy level substantiates the conclusion that the neural network model employed in this study performs with considerable effectiveness and can be regarded as a dependable tool for language skill prediction in applied educational contexts.

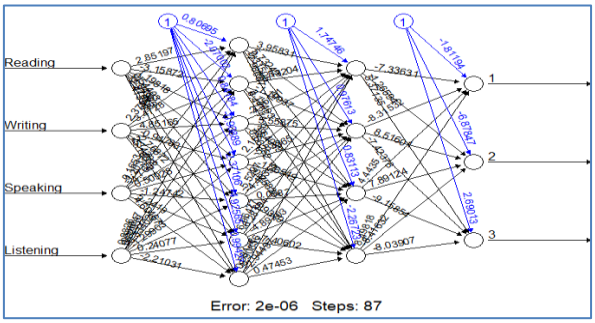


Figure 3. Neural Network Model Visualization

Figure 3 presents a visual illustration of the neural network architecture developed to predict language skill outcomes based on four primary input variables: Reading, Writing, Speaking, and Listening. The model operates through a network-based structure in which information from each input variable is processed sequentially through hidden layers before reaching the output layer, enabling the network to capture and represent nonlinear relationships between inputs and predicted outcomes. This architectural design allows the model to move beyond linear assumptions and approximate complex patterns within the data with greater fidelity. The primary objective of the neural network in this study is to classify students' language proficiency based on their performance across the four skill dimensions, with the resulting classifications subsequently serving as a basis for cross-validation of further analysis within the clustering framework.

At the input layer, the four main variables (listening, speaking, reading, and writing) represent the language skills that serve as the initial input to the model. These variables are then passed to the hidden layers, where information is processed through the connections between neurons, each associated with specific weights. These weights, as shown in the visualization, represent the influence of one neuron on another, either positively or negatively. The hidden layers are tasked with identifying deep patterns in the data that may not be visible through simpler analytical methods. Thus, the model can capture multivariate relationships between the language skills.

At the output layer, there are three nodes representing the predicted categories, likely related to the clustering of students' language proficiency levels. This process allows the NN to map input data into specific groups based on the patterns it has learned during training. The 87 steps indicate that the model has achieved convergence efficiently, where the changes in weights and biases are minimal after the final iteration. This reflects the stability of the model in learning data patterns.

The error value of 2e-06 indicates a very small error rate, confirming that the model achieved extremely high accuracy in predicting students' language skills. The low error rate reflects that the NN has matched predictions with actual data almost perfectly. This strengthens the model's validity in processing data and generating reliable prediction outcomes. The visualization of weights between neurons also provides additional insights into the contribution of each input variable to the final result, where larger weights indicate more significant relationships.

Collectively, these results indicate that the neural network model demonstrates both effectiveness in learning complex data patterns and efficiency throughout its training process. The model exhibits considerable promise for deployment in educational settings, particularly in the analysis and classification of students' language competencies across multiple dimensions. By leveraging the predictive outputs and accompanying visualizations, this study makes a meaningful contribution toward the advancement of technology-driven methodologies for language proficiency assessment and instructional improvement within academic contexts. These outcomes lend support to the proposition that neural network modelling constitutes a reliable analytical approach for comprehensively capturing the intricacies inherent in multivariate educational data.

The cluster analysis identified three groups of students based on their proficiency in reading, writing, speaking, and listening skills in Arabic, representing low, intermediate, and high levels of performance. This distribution indicates that language proficiency within the sample is structured along a gradual performance continuum rather than forming sharply differentiated competency types. The grouping highlights the variability of students' language abilities across the four core skills and suggests that overall proficiency tends to develop progressively across multiple dimensions of language competence. Such a structure provides a clearer picture of how language performance is distributed within the student population and allows the identification of meaningful patterns in multidimensional assessment data.

Similarly graded proficiency patterns have been reported in studies on language learning analytics, wherein learner achievement across multiple language skills often follows hierarchical levels of development. However, previous studies have frequently relied on conventional clustering or descriptive grouping techniques that assign learners exclusively to a single category.[19] By applying fuzzy clustering, the present study offers a more flexible representation of language

[19] Yu-Jie Wang et al., "A Data-Driven Precision Teaching Intervention Mechanism to Improve Secondary School Students' Learning Effectiveness," *Education and Information Technologies* 29, no. 9 (2024): 11645–73, https://doi.org/10.1007/s10639-023-12238-x.

proficiency by allowing partial membership across clusters, thereby reflecting the gradual and multidimensional nature of language development more faithfully.[20] From a pedagogical perspective, these findings are consistent with adaptive learning principles, which emphasize the use of data-driven learner profiling to guide instructional strategies and personalize learning pathways. Consequently, the clustering results not only describe variations in student performance but also provide a basis for identifying instructional priorities, such as targeted reinforcement for students with lower proficiency and differentiated learning opportunities for learners demonstrating higher levels of competence.[21]

Beyond the visual grouping, statistical testing further examined whether the clusters represented meaningful differences in language proficiency. The ANOVA results indicated significant differences among clusters across all four language skills, with moderate to large effect sizes. These results suggest that cluster membership corresponds to substantial variations in student performance rather than arbitrary group assignments.[22] Although the clustering procedure itself organizes students based on similarity patterns, the statistical analysis provides additional evidence that the identified groups reflect meaningful distinctions in proficiency levels within the observed dataset.[23]

The spatial distribution of the clusters in a two-dimensional representation generated through dimensionality reduction further illustrates the internal structure of the dataset.[24] The relatively clear separation among clusters indicates that the language skill indicators contain sufficient variation to support meaningful grouping patterns. Similar findings have been reported in educational data mining research, where clustering techniques have been shown to reveal latent learning structures in multivariate performance data.[25] In the context of Arabic language assessment, this pattern suggests that multidimensional skill indicators can provide useful insights into how variations in learner proficiency are organized within the student population.

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[20] Guang Li et al., "Research on the Natural Language Recognition Method Based on Cluster Analysis Using Neural Network," *Mathematical Problems in Engineering* 2021 (May 2021): 1–13, https://doi.org/10.1155/2021/9982305.

[21] Fei Teng, "Fuzzy Association Rule Mining for Personalized Chinese Language and Literature Teaching from Higher Education," *International Journal of Computational Intelligence Systems* 17, no. 1 (2024): 266, https://doi.org/10.1007/s44196-024-00676-5.

[22] XiuHua Zhao, "A Hybrid Deep Learning and Fuzzy Logic Framework for Feature-Based Evaluation of English Language Learners," *Scientific Reports* 15, no. 1 (2025): 33657, https://doi.org/10.1038/s41598-025-17738-z.

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[24] Youngjoo Kim et al., "Visual Cluster Separation Using High-Dimensional Sharpened Dimensionality Reduction," *Information Visualization* 21, no. 3 (2022): 197–219, https://doi.org/10.1177/14738716221086589.

[25] Ilyas Supena et al., "The Influence of 4C (Constructive, Critical, Creativity, Collaborative) Learning Model on Students' Learning Outcomes," *International Journal of Instruction* 14, no. 3 (2021): 873–92, https://doi.org/10.29333/iji.2021.14351a.

In addition to cluster analysis, this study also integrates Artificial Neural Networks (ANN) to predict proficiency based on the same data. With an error value of 2e-06 and a model accuracy of 0.933333, the ANN demonstrates excellent performance in learning the relationships between variables. This model not only identifies linear relationships but also non-linear patterns that are often difficult to capture by traditional analytical methods such as multiple linear regression. These results align with recent findings by Zareef, who highlighted the ANN's ability to process educational data with high complexity.[26] The application of ANN in this study underscores the importance of integrating artificial intelligence technology in educational analysis to produce accurate and relevant predictions that can inform instructional decision-making.[27]

The prediction results from the ANN model also serve as validation for the clustering results, as the distribution patterns generated by both approaches support each other. This integration strengthens the argument that data-driven analysis, such as ANN and clustering, can complement each other to provide a more comprehensive understanding of student abilities. Recent studies by Kocher & Kumar, support the importance of this hybrid approach, showing that the use of machine learning techniques in educational analysis can provide new insights that cannot be obtained with conventional methods alone.[28] This also contributes to addressing the challenges of big data analysis in the modern educational context.[29]

From a methodological perspective, the integration of fuzzy clustering and predictive modeling offers a structured analytical pathway for competency profiling.[30] While clustering reveals latent group structures, predictive modeling examines the strength and direction of relationships among multidimensional skill indicators in relation to overall academic achievement.[31] This dual approach not only enhances interpretability but also increases analytical rigor by combining exploratory and predictive techniques within a single framework. Consequently, the study demonstrates how educational data mining can move beyond descriptive

[26] Muhammad Zareef et al., "An Overview on the Applications of Typical Non-Linear Algorithms Coupled With NIR Spectroscopy in Food Analysis," *Food Engineering Reviews* 12, no. 2 (2020): 173–90, https://doi.org/10.1007/s12393-020-09210-7.

[27] Adriano Bressane et al., "Understanding the Role of Study Strategies and Learning Disabilities on Student Academic Performance to Enhance Educational Approaches: A Proposal Using Artificial Intelligence," *Computers and Education: Artificial Intelligence* 6 (June 2024): 100196, https://doi.org/10.1016/j.caeai.2023.100196.

[28] Geeta Kocher and Gulshan Kumar, "Machine Learning and Deep Learning Methods for Intrusion Detection Systems: Recent Developments and Challenges," *Soft Computing* 25, no. 15 (2021): 9731–63, https://doi.org/10.1007/s00500-021-05893-0.

[29] Christian Fischer et al., "Mining Big Data in Education: Affordances and Challenges," *Review of Research in Education* 44, no. 1 (2020): 130–60, https://doi.org/10.3102/0091732X20903304.

[30] Antonio Pacifico, "Fuzzy Clustering with Robust Learning Models for Soccer Player Profiling and Resilience Analysis," *Journal of Big Data* 12, no. 1 (2025): 263, https://doi.org/10.1186/s40537-025-01297-1.

[31] Li Zhang and Xueying Gu, "A Novel Career Prediction Method Based on Fuzzy Model—Fuzzy Clustering Approach," *Acta Psychologica* 259 (September 2025): 105475, https://doi.org/10.1016/j.actpsy.2025.105475.

analysis toward more evidence-based and statistically supported profiling practices in language assessment contexts.[32]

This study has significant implications both theoretically and practically. Theoretically, the findings support the development of a technology-based adaptive learning model as proposed by Liu.[33] Practically, these findings can be used to design adaptive learning programs tailored to the needs of students in each cluster.[34] Such programs allow for real-time feedback based on ANN predictions, thereby enhancing the effectiveness of the learning process. Additionally, these findings provide a foundation for developing collaborative learning strategies, where students with high proficiency can act as mentors for students with lower proficiency, strengthening community-based learning approaches and fostering peer-assisted learning environments.[35]

The combined application of cluster analysis and artificial neural networks in this study reveals a productive analytical synergy in understanding and addressing variability in student language proficiency. By merging data-driven grouping procedures with advanced predictive modeling, this integrated approach not only illuminates the internal structure of learner abilities but also generates practically actionable insights for designing adaptive and collaborative instructional strategies. These findings highlight the transformative capacity of incorporating artificial intelligence into educational research, opening pathways for innovative solutions aimed at enhancing learning quality and narrowing proficiency gaps among diverse student populations. In a broader sense, this study contributes to ongoing scholarly discourse on technology-enhanced education, advancing the case for more personalized and effective pedagogical methodologies suited to the demands of contemporary academic environments.

Conclusion

The results of this study indicate that combining Fuzzy C-Means clustering with neural network modeling yields a productive analytical framework for competency profiling in Arabic language assessment. Through clustering procedures, three proficiency groupings were distinguished: low, moderate, and high on the basis of student performance across reading, writing, speaking, and listening domains. These groupings expose a graded proficiency structure within the sampled population and provide an empirical lens through which the

[32] Guldana A. Begimbetova et al., "Applying Unsupervised Possibilistic Fuzzy C-Means to Cluster Teachers' Online Practices," *Journal of Innovation in Educational and Cultural Research* 6, no. 3 (2025): 558–66, https://doi.org/10.46843/jiecr.v6i3.2297.

[33] Na Liu et al., "Optimization of Online Learning Resource Adaptation in Higher Education through Neural Network Approaches," *International Journal of Interactive Mobile Technologies (iJIM)* 18, no. 11 (2024): 92–107, https://doi.org/10.3991/ijim.v18i11.49779.

[34] Emmanuel Okewu et al., "Artificial Neural Networks for Educational Data Mining in Higher Education: A Systematic Literature Review," *Applied Artificial Intelligence* 35, no. 13 (2021): 983–1021, https://doi.org/10.1080/08839514.2021.1922847.

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distribution of multidimensional language abilities among learners can be examined. The predictive modeling component further demonstrates that interrelationships among language skill indicators are amenable to machine learning techniques, offering additional analytical insight into how discrete language competencies collectively contribute to overall academic outcomes.

Several limitations warrant consideration when interpreting these findings. The dataset was cross-sectional in nature and drawn exclusively from a single academic program at one institution, a constraint that may restrict the extent to which conclusions can be generalized to broader educational populations. Furthermore, the analysis was confined to four core language skills, leaving aside potentially influential variables such as cognitive capacities, motivational orientations, or learning behavior patterns that may also shape language achievement. The absence of qualitative data to complement the quantitative findings also limits the depth of interpretation regarding learners' experiences and the contextual factors influencing their proficiency profiles.

Subsequent research endeavors could broaden the scope of this framework by applying it across varied educational settings, integrating additional linguistic and cognitive variables, and utilizing longitudinal data to assess the temporal stability of identified proficiency profiles. Such extensions would deepen the field's understanding of Arabic language proficiency dynamics and reinforce the utility of data-driven methodologies in language assessment scholarship.

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Author Contribution Statement

AM contributed to the conceptualization of the study and data collection. AD designed the research methodology, conducted the data analysis, and drafted the manuscript. AWR supervised the analytical framework, validated the statistical procedures, and critically revised the manuscript for important intellectual content. DH and SM contributed to manuscript review and proofreading. All authors reviewed and approved the final version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

AI Writing Statement

The authors used Claude AI to assist with language editing, helping to improve clarity and coherence throughout the manuscript. Additionally, Perplexity AI was

employed to identify and retrieve relevant journal references aligned with the scope and focus of this research. All AI-generated suggestions and outputs were critically evaluated and revised by the authors to ensure accuracy, contextual appropriateness, and scholarly integrity. The authors take full responsibility for the final content presented in this manuscript.

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