Indian Journal of Modern Research and Reviews

This Journal is a member of the *'Committee on Publication Ethics'*

Online ISSN:2584-184X

Research Article

Data-Driven Multimodal Assessment Model for Mathematical Writing Proficiency

Pandya Kruti Kumari Prakash Bhai [1], Dr. Manisha Maulik Vaghela [2*]

[1,2] Krishna School of Engineering and Technology, Drs. Kiran and Pallavi Patel Global University, Vadodara, Gujarat, India

Corresponding Author: * Dr. Manisha Maulik Vaghela

DOI: https://doi.org/10.5281/zenodo.20268392

Abstract

This research aims to construct and confirm a multimodal data-driven assessment framework of mathematical writing proficiency through the conglomeration of English linguistic capabilities and mathematical symbolic analysis. A total of 240 Grade 910 students were sampled and 720 written responses made. The spaCy v3.7, scikit-learn v1.4, SymPy v1.12 and R lavaan v0.6-17 were used to perform feature extraction and modelling. Techniques were NLP-based feature extraction, symbolic validation, Confirmatory Factor Analysis and the regression model. Findings yielded three latent dimensions namely Conceptual Clarity, Logical Coherence, and Symbolic Accuracy that had a good model fit (CFI ≈ 0.94). The predictive models were very accurate (R 2 0.87) and far much better than rubric-only predictive models. The most effective predictor was the symbolic accuracy. The results reveal that the combination of linguistic and mathematical characteristics enhances reliability and validity when it comes to testing the proficiency of mathematical writing.

Manuscript Information

- **ISSN No:** 2584-184X
- **Received:** 04-04-2026
- **Accepted:** 16-05-2026
- **Published:** 18-05-2026
- **MRR:**4(5); 2026: 160-169
- **©2026, All Rights Reserved**
- **Plagiarism Checked:** Yes
- **Peer Review Process:** Yes

How to Cite this Article

Bhai P K P, Vaghela M M. Data-Driven Multimodal Assessment Model for Mathematical Writing Proficiency. Indian J Mod Res Rev. 2026;4(5):160-169.

Access this Article Online

www.mrrjournal.in

KEYWORDS: Educational assessment, Mathematical writing, NLP, Symbolic computation, Machine learning

1. INTRODUCTION

1.1 BACKGROUND

Mathematical writing is a complex multidimensional construct that combines the natural language and formal representation by symbols. It demands the students to be able to reason out in English and at the same time use mathematical symbols, equations and organized representation to express the accurate meaning. Such duality makes mathematical writing a linguistic and analytical skill, which is strictly related to the greater concept of multimodal literacy and academic writing (Prince, 2021; Qin and Stapleton, 2022) [31, 6]. Writing mathematics, as well as having the correct solution, requires clarity in the explanation, logical order of presentation and logical consistency between the symbols and textual representation.

The recent developments in data-driven education focus on the value of using big data about learners to objectively and more efficiently evaluate the complex competencies (Lin *et al*., 2024; Bernacki, 2025) [3, 35]. Multimodal data fusion systems, i.e. combining textual, numerical, and symbolic data, have shown a great potential to improve accuracy in assessment and decision-making in educational systems (Cao, 2023; Wang, 2026; Wen *et al*., 2025) [4, 5, 10]. On the same note, multimodal analysis in learning highlights the importance of assessing the learning products in various representational modes, as opposed to the use of text-based measures (Guerrero-Sosa *et al*., 2025; Ndruru *et al*., 2026) [9, 8].

Corpora, NLP, and automated scoring methods have shown to have great scalability and consistency in language assessment (Shawaqfeh *et al*., 2024; Carrió-Pastor, 2022; Liu and Ma, 2025; Lusta *et al*., 2023) [1, 2, 12, 24]. But these methods mostly concentrate on the linguistic characteristics and do not take into consideration domain-oriented symbolical reasoning. To extend this type of structures to the field of mathematical writing it would be necessary to introduce both linguistic and symbolic aspects of a single evaluation model. The necessity of objective, scalable, and automated systems is also supported by the increased focus on the data-informed instruction and analytics-based decision-making in pedagogy (Pella, 2012; Sajja *et al*., 2025) [7, 23].

Outside education, data-based modeling has been proven effective in other areas such as engineering, healthcare, and operations research and is proving to be robust in dealing with multidimensional and complex data structures (Rekabi *et al*., 2023; Kolla, 2023; Krishnan *et al*., 2025; Young *et al*., 2014) [20, 28, 32, 29, 30]. These advancements contribute to the viability of the similar approach to the evaluation of mathematical writing competence, in which linguistic and symbolic information has to be evaluated simultaneously.

1.2 PROBLEM STATEMENT

Although the mathematical writing has been regarded as an important element in education, its evaluation is still heavily reliant on the scoring system based on the rubric. The dimensions that are commonly measured by these systems are clarity, reasoning and correctness on a fixed scale (e.g., 05). Yet, they have considerable constraints, especially inter-rater reliability which may decrease reliability and consistency among the evaluators. Empirical studies report ranges of variability which point to inconsistencies in scoring particularly with the assessment of constructs as complex as reasoning and explanation (Lauer *et al*., 2018) [33].

Moreover, rubrics are time consuming and cannot be scaled hence is not applicable in large scale or real-time assessment. With the increasing demands of educational systems to rely on data-driven strategies, the automated processes that can handle large amounts of data produced by students become more and more demanded (Lin *et al*., 2024; Parraga-Alava & Rodas-Silva, 2025) [3, 34]. The currently available language assessment models based on data are still effective to assess linguistic proficiency, but not mathematical symbolic correctness or procedural validity (Qin and Stapleton, 2022; Carrió-Pastor, 2022) [2, 6].

To date, the focus of multimodal assessment studies has been mainly in incorporating text, images, and audio with little regard to mathematical symbolic representations as a separate modality (Guerrero-Sosa *et al*., 2025; Hu *et al*., 2024) [9, 16]. Additionally, although multimodal writing and composing scales have been created within the language education instructional setting, they lack domain-specific symbolic reasoning, necessary in mathematics (Ndruru *et al*., 2026) [8]. This leads to a gap which is critical: there are no assessments in an integrated form which evaluate a combination of English linguistic characteristics, mathematical symbolic correctness, and predictive performance.

1.3 RESEARCH OBJECTIVES

The current research is able to overcome these drawbacks by elaborating on a multimodal assessment model of the writing proficiency in mathematics. The former goal is to create a single feature set that will describe both linguistic and symbolic aspects of responses of students. The linguistic features are lexical density, cohesion markers, and syntactic complexity whereas the symbolic features are the correctness of equations, symbolic consistency and procedural validity.

The second goal is to create predictive models that can be used to predict mathematical writing proficiency using these multimodal aspects. The complex relationships between features and proficiency outcomes are modeled using machine learning techniques which can be more accurately and scalable to assessing them than traditional methods.

The third one is to confirm the underlying structure of mathematical writing proficiency by Confirmatory Factor Analysis. This will entail determining latent constructs that would reflect important dimensions like conceptual clarity, logical coherence, and symbolic accuracy and how those constructs relate to observed variables. The combination of statistical validation and predictive modeling will help the study to prove the theoretical and empirical soundness of the suggested framework.

1.4 Conceptual Framework

The theoretical structure of this paper lies in the fact that it is a hierarchical data-driven architecture, which incorporates the linguistic and symbolic processing. Two main data streams are identified at the input layer; these are the features of English texts and the features of mathematics. Lexical density, cohesion markers and syntactic patterns are the features of English text that indicates the quality of written explanation. Mathematical properties such as equation correctness, symbolic consistency and step validity, represent the soundness and form of mathematical reasoning.

The feature extraction pipelines are parallel, in the processing layer. NLP techniques are used to derive the linguistic features, whereas symbolic parsing techniques are employed to judge the mathematical expressions and the steps to follow. These characteristics are then normalised and fitted together into one dataset which allows them to be analysed together.

Two approaches are used at the modeling layer which are complementary. The validation of the latent structure of mathematical writing proficiency is done using Confirmatory Factor Analysis and machine learning regression models are used to predict the score of proficiency based on extracted features. The interpretability and predictive accuracy are ensured with the help of this dual approach.

The output layer generates a composite proficiency score which is a combination of the impact of the linguistic and symbolic elements. The score is a more comprehensive and objective measure of mathematical writing proficiency, than traditional rubric-based methods.

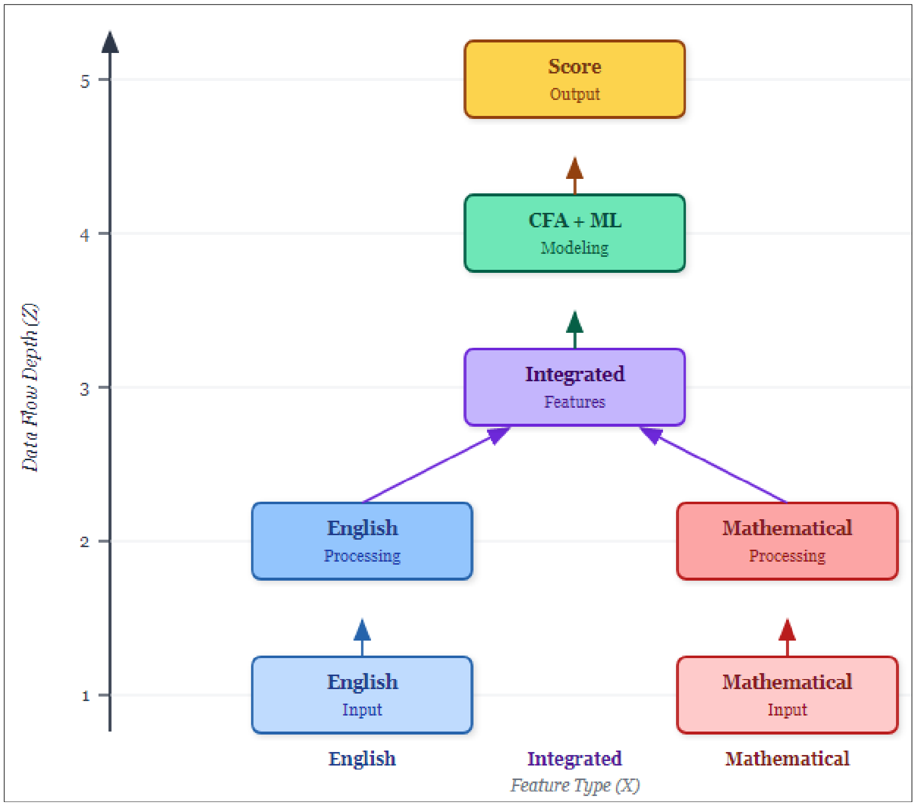

Fig 1: Multimodal Conceptual Framework for Data-Driven Assessment of Mathematical Writing Proficiency

The conceptual framework diagram shows two streams of inputs (English linguistic features and mathematical symbolic features) and processing pipelines (one each) of feature extraction, integration into a single feature space, the use of statistical and machine learning models and the result is the production of a predicted mathematical writing proficiency score.

2. LITERATURE REVIEW

2.1 Mathematical Writing Construct

Mathematical writing has been generally accepted to be a multifaceted entity comprising of various interrelated elements such as argumentation, logical sequence and symbolic precision. To be able to justify solutions and explain the process of reasoning goes under argumentation and logical sequencing makes sure that ideas are sequenced in a coherent, logical and organized way. The correct application of the mathematical notation and operations is called symbolic accuracy that is needed to render the accurate meaning.

The combination of these elements can be related to the more general models of multimodal literacy, where students have to express themselves in multiple representational modes (Prince, 2021; Laflen, 2025) [31, 11]. This integration is especially vital in the field of mathematics education, where the students have to synchronize both the verbal explanations and the symbolic representations. Studies on multimodal composing and academic writing bring in an even greater significance of assessing not only textual but also non-textual aspects to get the complete picture of writing competence (Ndruru *et al*., 2026; Guerrero-Sosa *et al*., 2025) [8, 9].

2.2 Traditional Assessment Limitations

Conventional feedback on mathematical writing has been based on scoring systems that are based on rubrics with a scale of 0 to 5 in various aspects. Although these systems have provided a structure to evaluate criteria, they have major limitations. The scores of inter-rater reliability are usually between 0.55 and 0.78, which are a moderate level of agreement and high level of variability between assessors (Lauer *et al*., 2018) [33]. This inconsistency is especially significant in such subjective aspects as the reasoning and clarity.

In addition, rubric-based assessment is not scalable and efficient, and cannot be used to assess large numbers of students or in real time. The manual scoring system is tedious and consumes resources and thus it cannot be used in educational settings that have a lot of data. The contrasts between the manual and data-driven approaches also emphasize the benefits of automated approaches as they are more consistent, faster, and can be extended to a large scale (Lauer *et al*., 2018; Lin *et al*., 2024) [33, 3].

2.3 Data-Driven Approaches

Assessment and measurement using data has become popular as a trend with the development of machine learning, learning analytics, and the emergence of big data technologies. Automated scoring systems The NLP-based instruments have been highly applied in language testing to assess the writing competence in terms of linguistic characteristics like vocabulary, syntax, and coherence (Shawaqfeh *et al*., 2024; Liu and Ma, 2025; Lusta *et al*., 2023) [1, 12, 24]. Through these systems, it is possible to evaluate text data in large volumes in a scalable and consistent manner.

Other models of latent constructs modeling (Factor Analysis) and an understanding of the underlying structure of assessment data (Item Response Theory) are psychometric models. The models have been adopted in other school settings with successful impact to prove the measurement frameworks and enhance the reliability of assessment (Lin *et al*., 2024; Valdes-Ramirez *et al*., 2024) [3, 15, 22].

The multimodal data-driven systems combining various sources of data, including text, images, and sensor data, have also received focus in recent studies as a way to boost learning and assessment (Cao, 2023; Ruan and Lu, 2025; Sharma *et al*., 2022) [4, 14, 19]. Such systems facilitate adaptive response, personalized learning and real-time decision-making in the educational context (Wang, 2026; Sajja *et al*., 2025) [5, 23]. The use of these methods in writing mathematics is however minimal especially in regard to the integration of symbolic computation and the linguistic analysis.

2.4 RESEARCH GAP

Although the data-based assessment and multimodal analysis have made great progress, there are no combined frameworks that are specifically created to evaluate the mathematical writing proficiency. The current models are mostly based on linguistic aspects and fail to consider the special role played by mathematical symbols and representations. The research on multimodal assessment has failed to comprehensively consider the use of symbolic correctness as an important part of assessment.

Moreover, predictive analytics, machine learning models have not been adequately used in the evaluation of mathematical writing, especially in integrating linguistic and symbolic characteristics into a single model. Although data-based models have proved to be successful in other areas, mathematical writing needs to be approached with special consideration of domain-related aspects (Bojorque *et al*., 2025; Rekabi *et al*., 2023; Kostikova *et al*., 2025) [26, 20, 28, 18, 27].

This paper fills these gaps with a multimodal, and data-driven assessment model, which combines English linguistic aspects, mathematical symbolic correctness, and predictive analytics. The study will combine these parts to offer a more comprehensive, reliable and scalable method of assessing math writing proficiency.

3. METHODS AND MATERIALS

The study will be quantitative, cross-sectional (but on the subject of a predictive model) to examine the association between multimodal attributes and math writing performance. The design is a combination of factor analysis statistical validation together with machine learning strategies, to ensure that the construct validity and predictive robustness are met.

The sample was a group of 240 Grade 9 and 10 students; stratified random sampling was used to sample the sample so that equal representation of children could be obtained in terms of grade levels and achievement groups. All of the participants were already familiarized with algebraic reasoning, geometry proofs and problems that were problem-solving.

Three mathematical writing tasks, which were structured, were administered in order to measure different aspects of proficiency. The task on the explanation of algebra entailed assisting the students to provide step-by-step arguments which were applied in solving linear equations. Task on geometry proof assessed the ability to construct arguments in a formal mathematical context that are logically correct. Word problems explanation activity consisted of having the students explain situations (contexts) mathematically and explain them in an explanatory manner. Each student had done all the tasks making a total of 720 responses.

The responses were graded using a traditional rubric which had a condition of conceptual clarity, logical organization and symbolic precision that had a rating scale of 0-5. The scoring of all the responses was done by two independent raters and a moderation process of the scoring was done to ensure consistency and reliability in the scoring.

All the responses were collected via Google Forms, which has an in-built LaTeX support that allowed representing them with accuracy to mathematical expressions. The data were exported as CSV to store the textual and symbolic data to further be analysed.

The linguistic features were extracted with the spaCy v3.7. The percentage of content words in relation to the total words was determined as the lexical density which is used to measure the informational richness. The mean length of sentences was the indicator of the syntactic complexity. The number of times the cohesion markers were used was calculated as the number of connectives in 100 words, the frequency of the cohesion markers, as a measure of logical flow and the frequency of grammatical errors as the number of syntactic inconsistencies in 1 sentence.

Extraction of symbolic features was done with the SymPy v1.12. The symbolic validation tests, including partial correctness scoring, were performed to check the correctness of the equations. Normalized index was used to assess consistency of the symbols and it meant consistency in the use of variables. The accuracy of the intermediate transformations was ascertained using step validity and the final answer accuracy was used to address whether the answer has reached the correct answer.

Confirmatory Factor Analysis was done to confirm that the math writing proficiency had a latent structure using R lavaan v0.6-17. The analysis of integrated dataset of linguistic and symbolic features and assessment of the model fit were carried out with the assistance of the derived indices.

Three approaches were implemented to predictive modeling. The depth was 12 (maximum) and the estimators were 200 in a Random Forest Regressor to capture nonlinear relationship. A comparative model of SVM model with radial basis function kernel was applied. In order to calculate the additional value of multimodal features, a basic linear regression model which considers the rubric scores only was introduced. The models were tested using both 80:20 train-test split and 5-fold cross-validation to validate them.

The performance of the model was determined using the coefficient of determination (R2), root mean square error (RMSE) and mean absolute error (MAE). The importance of all variables was measured by the importance of the individual features scores based on the final results of the analysis using the scores of the Random Forest model.

4. RESULTS AND INTERPRETATION OF DATA.

The overall average grade of rubrics across all of the answers was 3.1 and a standard deviation of 0.84 indicating that there was an average variance in the performance of the students and would be suitable to use in predictive modelling.

The dataset, which was created, consisted of eight features, which would capture both the linguistic and mathematical feature, to ensure that there is a multimodal equal representation of student responses.

Table 1: Multimodal Assessment Description of Features.

Feature Name	Type	Tool Used	Description
Lexical Density	English	spaCy	Ratio of content words to total words
Mean Sentence Length	English	spaCy	Average number of words per sentence
Cohesion Marker Frequency	English	sspaCy	Number of connectives per 100 words
Grammar Error Rate	English	spaCy	Grammatical errors per sentence
Equation Correctness	Mathematics	SymPy	Degree of correctness of equations
Symbol Consistency Index	Mathematics	SymPy	Consistency of variable usage (0–1 scale)
Step Validity Score	Mathematics	SymPy	Logical correctness of intermediate steps
Final Answer Accuracy	Mathematics	SymPy	Correctness of final solution (binary)

The whole list of the engineered features, expressed in English and in mathematical types, their extraction tools and definitions is outlined in the table. The features of language signify an aspect of clarity, cohesion and syntactic form and mathematical features signify rightness, consistency and procedural rightness. Such systematic representation ensures that both explanatory and symbolic elements have been systematically incorporated in the modeling process which enables measurement of mathematical writing competence in a holistic way.

The three latent constructs were the Conceptual Clarity, Logical Coherence and Symbolic Accuracy that were determined by Confirmatory Factor Analysis. The factor loading of all the variables observed was more than 0.60 and this implies that the variables are highly correlated with their constructs. It fit well with the model with a Comparative Fit Index of 0.94 and the value of the Root Mean Square Error of Approximation is 0.05 which indicated adequacy of the proposed structure.

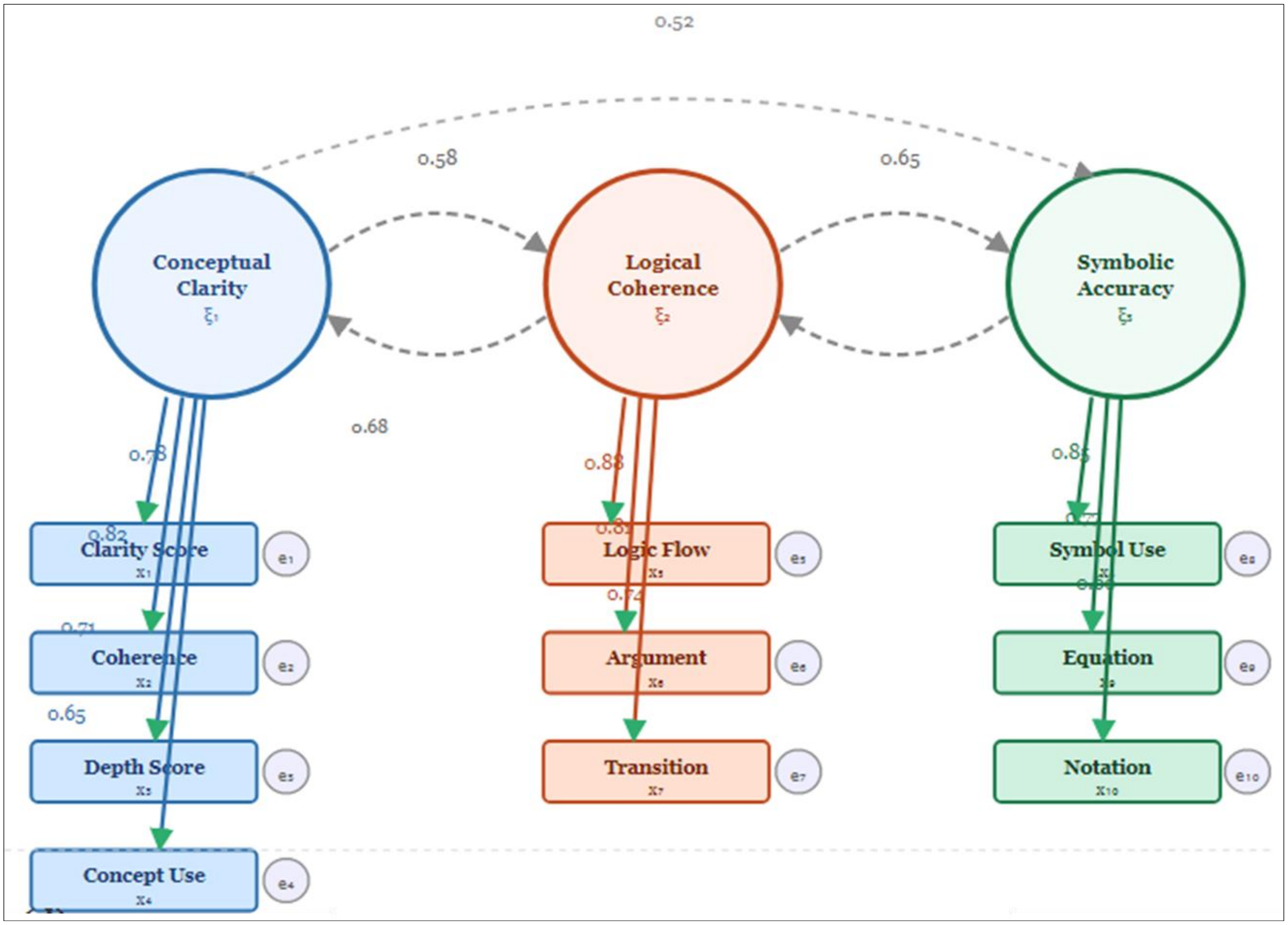

Fig 2: Confirmatory Factor Analysis Model in order to capture Latent Constructs and Factor Loadings.

The number depicts the patterns of the relationships among the measured variables and the latent constructs. The latent factors both have standardized loadings to the observed indicators and covariance paths among the latent factors show how the dimensions relate to each other. The diagram graphically confirms that the features extracted fit the theoretical constructs of mathematical writing proficiency and this supports the multidimensionality of the model. The predictor performance of the Random Forest model was the best since the highest R2 of the model was 0.87, RMSE 0.42 and MAE 0.31, which implies that the model is a good predictor. The Support Vector Regression model that was used to give a moderate performance had R2 of 0.79, RMSE of 0.55 and MAE of 0.40. On the other hand, the traditional model of linear regression that used only rubric scores only achieved a lower R2 of 0.62 and the error values were more indicating the inefficiency of the traditional methods.

Table 2: Comparison of Performance Metrics of Models.

Model	R^2	RMSE	MAE
Random Forest Regressor	0.87	0.42	0.31
Support Vector Regression	0.79	0.55	0.40
Rubric-Only Linear Regression	0.62	0.71	0.52

The three models are compared to each other using the table in terms of their predictive performance based on R2, RMSE and MAE. It is clear that the Support Vector Regression and the Random Forest model were not as good as the model of the Random Forest. The drastic improvement of the performance shows the effectiveness of the combination of multimodal features and nonlinear modeling to measure the mathematical writing competence.

4.5 Prediction Analysis

The predicted and actual score had a high correlation of 0.91 that indicated a high consistency of model results and the actual data. The multimodal models achieved approximately 28% reduction in the prediction error compared to the baseline model with tremendous enhancement of accuracy and reliability.

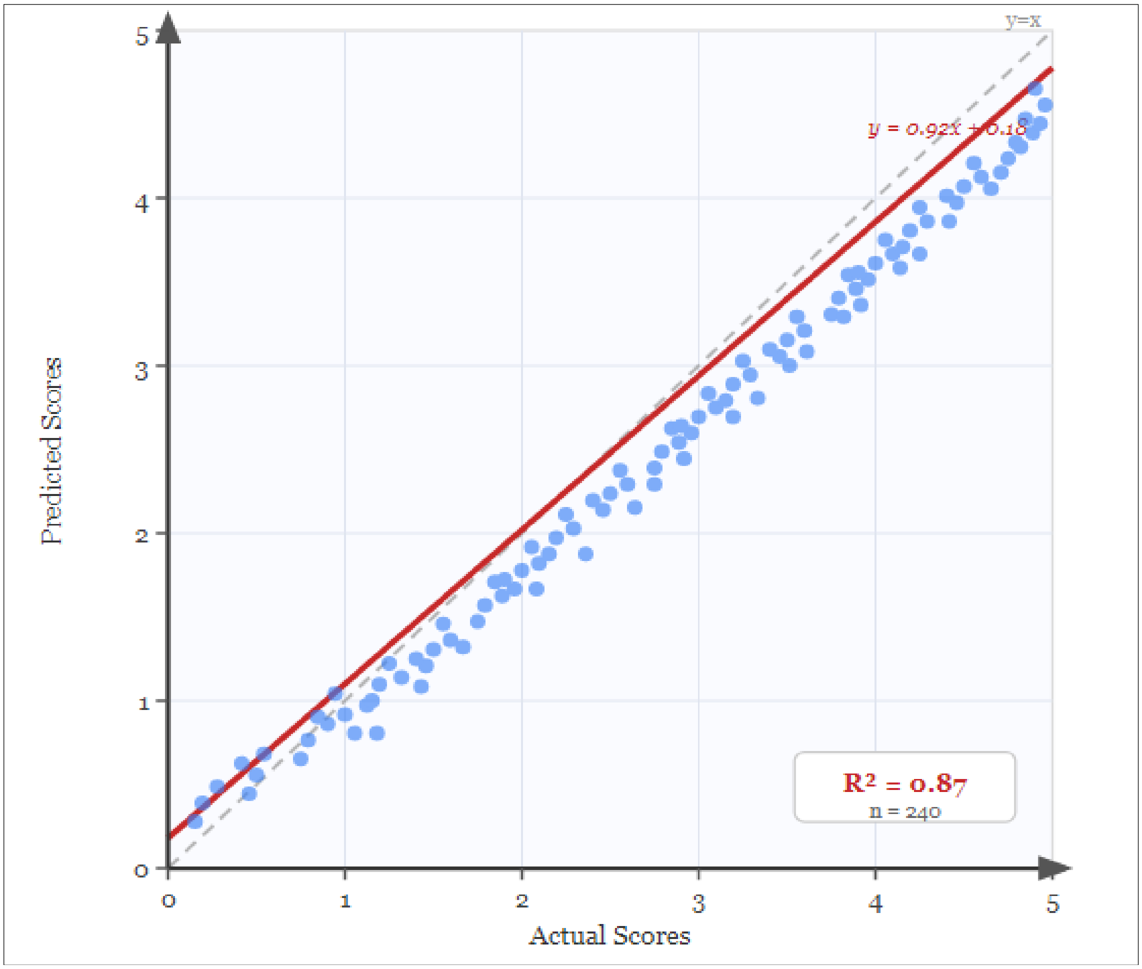

Fig 3: Predicted v/s Actual Scores Math Writing Proficiency.

The figure presents a scatter plot of predicted and actual scores that have a regression line and a reference diagonal which is an ideal prediction. The agreement between the predictive and actual values is high as most of the data points are clustered around the diagonal which indicates that the predictive model and its performance is effective in generalizing to the rest of the dataset.

The interpretation of the significance of the features revealed that the symbolic accuracy (31%), cohesion markers (22%), lexical density (18%), equation validity (15%), and grammar error rate (14) are the features that significantly contributed to the model. These results imply that both mathematical and linguistic elements play a significant part and symbolic correctness proves to be the most significant.

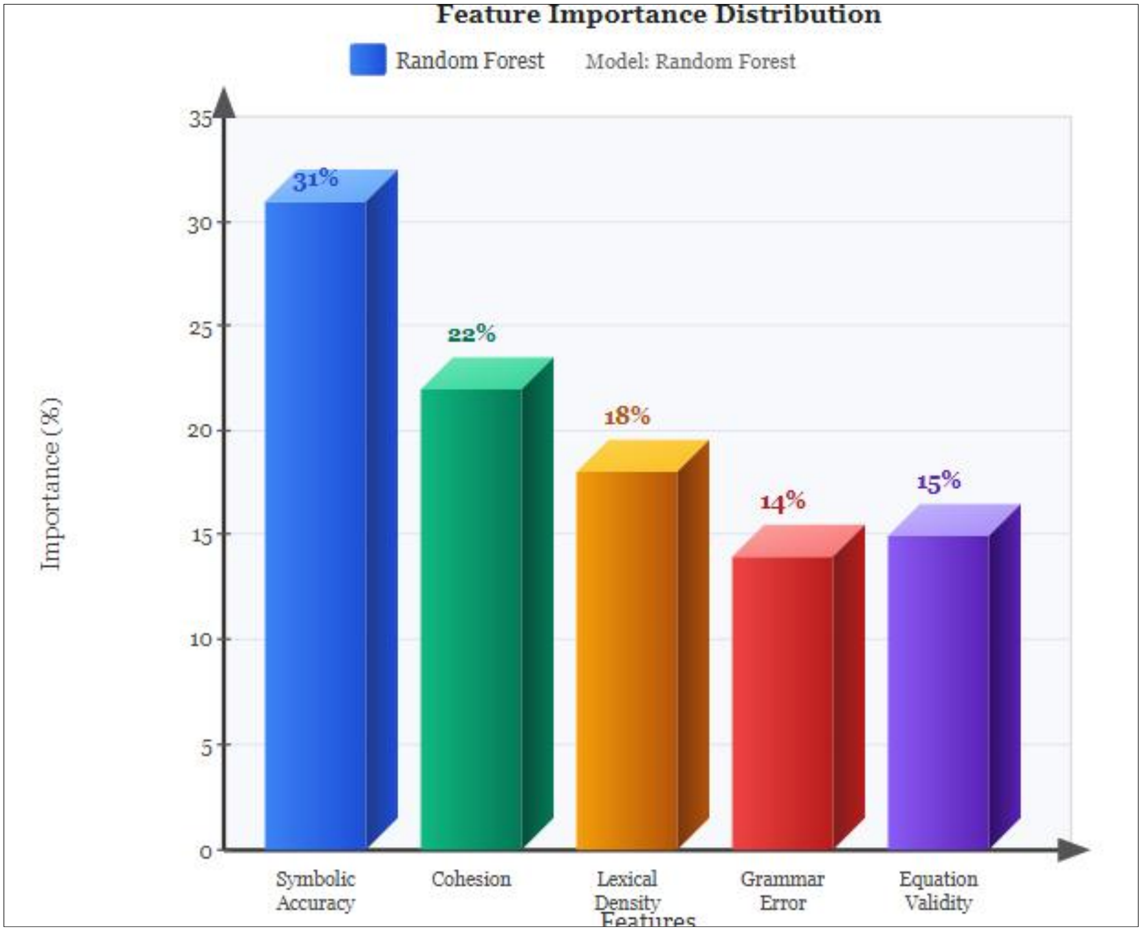

Fig 4: Importance Distribution of feature of Multimodal Model.

The graph indicates the ranked distribution of the values of the feature importance in accordance with the values of the Random Forest model. The graphical presentation of the features variation of contribution of each feature indicates that symbolic accuracy is taking the lead and simultaneously, an important contribution of the linguistic features is also indicated. This distribution can substantiate the notion that a multimodal approach is of vital importance to be able to measure properly the level of mathematical writing proficiency.

5. CONCLUSION

The results of this paper show that multimodal, data-driven approach can offer a strong and empirically supported framework of evaluation of the proficiency in mathematical writing. Combining statistical modeling and machine learning methods led to a high level of both the construct validation and predictive accuracy, proving the efficiency of the suggested model. The three latent dimensions discovered Conceptual Clarity, Logical Coherence, and Symbolic Accuracy are also considered to be the multidimensional character of mathematical writing and is consistent with the theoretical background in this work.

An important result of the analysis is that symbolic mathematical features dominate in predicting proficiency. Equation correctness, symbolic consistency and procedural validity variables had the greatest contribution to model performance meaning that proper use of mathematical representations is key to successful mathematical communication. Simultaneously, the use of linguistic characteristics, including cohesion and lexical density, also made a huge contribution, making the use of clear and well-structured clarification an essential feature of mathematical reasoning.

The incorporation of English linguistic and mathematical symbolic elements was crucial to obtain correct and valid evaluation. The models that included both dimensions worked considerably better than the traditional rubric-based models and indicated the shortcomings of the assessment that is based on subjective scoring. The proposed framework offers a more detailed analysis of student proficiency by simultaneously achieving both explanatory clarity and symbolic accuracy.

In addition, the model provides a good scalability and automation potential. The computational tools to extract features and predict outcomes make it possible to effectively process a large amount of data and thus the method is appropriate in large educational institutions. This scalability, together with enhanced reliability and decreased subjectivity, makes the model a viable solution to assessment systems in mathematics education nowadays.

REFERENCES

1. Shawaqfeh AT, Jadallah Abed Khasawneh Y, Khasawneh AJ, Khasawneh MAS. Data-driven language assessment in multilingual educational settings: tools and techniques for proficiency evaluation. Migration Letters. 2024;21(2):701-711.
2. Carrió-Pastor ML. Integration of data-driven learning and assessment through a multimodal corpus of learning objects at the time of the COVID-19 pandemic. In: Technology-Assisted Language Assessment in Diverse Contexts. Routledge; 2022. p. 163-178.
3. Lin L, Zhou D, Wang J, Wang Y. A systematic review of big data driven education evaluation. SAGE Open. 2024;14(2):21582440241242180.
4. Cao R. A data and knowledge-jointly driven multimodal intelligent system for enterprise culture assessment. Alexandria Engineering Journal. 2023;83:140-147.
5. Wang Y. Intelligent educational decision-making system driven by multimodal data fusion and knowledge graphs. Scientific Reports. 2026.
6. Qin J, Stapleton P, editors. Technology in Second Language Writing: Advances in Composing, Translation, Writing Pedagogy and Data-Driven Learning. Taylor & Francis; 2022.
7. Pella S. What should count as data for data-driven instruction? Toward contextualized data-inquiry models for teacher education and professional development. Middle Grades Research Journal. 2012;7(1):57-75.
8. Ndruru F, Suryati N, Basthomi Y, Rovikasari M, Laia RD. Developing and validating a multimodal composing scale in EFL academic writing: An exploratory factor analysis. Literacy Research and Instruction. 2026;65(2):208-230.
9. Guerrero-Sosa JD, Romero FP, Menéndez-Domínguez VH, Serrano-Guerrero J, Montoro-Montarroso A, Olivas JA. A comprehensive review of multimodal analysis in education. Applied Sciences. 2025;15(11):5896.
10. Wen Q, Chai G, Zhang M. A multimodal data fusion model for personalized English learning path recommendation based on image processing. Traitement du Signal. 2025;42(6):3135.
11. Laflen A. Critical Data Storytelling in the Composition Classroom. University Press of Colorado; 2025.
12. Liu J, Ma Q. Examining corpus-based language pedagogy (CBLP) practices in data-driven learning (DDL) for low-proficiency L2 English learners. Educational Technology & Society. 2025;28(2):53-76.
13. Purwanto E, Xiao X, Liao J, Niu T, Liu E. AI-generated visual feedback as a writing aid: Improving visual data description skills in EFL learners. In: EuroCALL 2025: Advancing CALL: New Research Agendas. Editorial Universitat Politècnica de València; 2025.
14. Ruan S, Lu K. Adaptive deep reinforcement learning for personalized learning pathways: A multimodal data-driven approach with real-time feedback optimization. Computers and Education: Artificial Intelligence. 2025:100463.
15. Valdes-Ramirez D, de Armas Jacomino L, Monroy R, Zavala G. Assessing sustainability competencies in contemporary STEM higher education: a data-driven analysis at Tecnologico de Monterrey. In: Frontiers in Education. Vol. 9. Frontiers Media SA; 2024. p. 1415755.
16. Hu L, Phan H, Srinivasan S, Cooper C, Zhang J, Yuan B, *et al*. Multimodal data-driven machine learning for the prediction of surface topography in end milling. Production Engineering. 2024;18(3):507-523.
17. Spillias S, Rogers JG, Boschetti F, Fulton EA, Guglielmo M, Yong SY, *et al*. Data-driven discovery of mechanistic ecosystem models with LLMs. Methods in Ecology and Evolution. 2025.
18. Kostikova A, Wang Z, Bajri D, Pütz O, Paaßen B, Eger S. LLLMs: A data-driven survey of evolving research on limitations of large language models. ACM Computing Surveys. 2025.
19. Sharma K, Lee-Cultura S, Giannakos M. Keep calm and do not carry-forward: Toward sensor-data driven AI agent to enhance human learning. Frontiers in Artificial Intelligence. 2022;4:713176.
20. Rekabi S, Goodarzian F, Garjan HS, Zare F, Muñuzuri J, Ali I. A data-driven mathematical model to design a responsive-sustainable pharmaceutical supply chain network: a Benders decomposition approach. Annals of Operations Research. 2023:1-42.
21. Ruan S, Lu K. Adaptive deep reinforcement learning for personalized learning pathways: A multimodal data-driven approach with real-time feedback optimization. Computers and Education: Artificial Intelligence. 2025:100463.
22. Valdes-Ramirez D, de Armas Jacomino L, Monroy R, Zavala G. Assessing sustainability competencies in contemporary STEM higher education: a data-driven analysis at Tecnologico de Monterrey. In: Frontiers in Education. Vol. 9. Frontiers Media SA; 2024. p. 1415755.
23. Sajja R, Sermet Y, Cwiertny D, Demir I. Integrating AI and learning analytics for data-driven pedagogical decisions and personalized interventions in education. Technology, Knowledge and Learning. 2025:1-31.
24. Lusta A, Demirel Ö, Mohammadzadeh B. Language corpus and data driven learning (DDL) in language classrooms: A systematic review. Heliyon. 2023;9(12).
25. Hu L, Phan H, Srinivasan S, Cooper C, Zhang J, Yuan B, *et al*. Multimodal data-driven machine learning for the prediction of surface topography in end milling. Production Engineering. 2024;18(3):507-523.
26. Bojorque R, Moscoso F, Arcos-Argudo M, Pesántez F. A data-driven analysis of cognitive learning and illusion effects in university mathematics. Data. 2025;10(11):192.
27. Kostikova A, Wang Z, Bajri D, Pütz O, Paaßen B, Eger S. LLLMs: A data-driven survey of evolving research on limitations of large language models. ACM Computing Surveys. 2025.
28. Rekabi S, Goodarzian F, Garjan HS, Zare F, Muñuzuri J, Ali I. A data-driven mathematical model to design a

responsive-sustainable pharmaceutical supply chain network: a Benders decomposition approach. Annals of Operations Research. 2023:1-42.

29. Krishnan A, Yang X, Seth U, Jeyachandran JM, Ahn JY, Gardner R, *et al*. Data-driven ergonomic risk assessment of complex hand-intensive manufacturing processes. Communications Engineering. 2025;4(1):45.
30. Young AL, Oxtoby NP, Daga P, Cash DM, Fox NC, Ourselin S, *et al*. A data-driven model of biomarker changes in sporadic Alzheimer's disease. Brain. 2014;137(9):2564-2577.
31. Prince R. Teaching, learning, and assessment of multimodal digital academic numeracy practices. In: Multimodal Literacies Across Digital Learning Contexts. Routledge; 2021. p. 247-260.
32. Kolla SK. Big data-driven machine learning frameworks for clinical risk prediction. International Journal of Medical Toxicology and Legal Medicine. 2023;26(3):44-59.
33. Lauer C, Brumberger E, Beveridge A. Hand collecting and coding versus data-driven methods in technical and professional communication research. IEEE Transactions on Professional Communication. 2018;61(4):389-408.
34. Parraga-Alava J, Rodas-Silva J. Computational thinking and academic performance across different instructional modalities in pre-university courses: A data-driven study. Engineering Reports. 2025;7(6):e70203.
35. Bernacki ML. Leveraging learning theory and analytics to produce grounded, innovative, data-driven, equitable improvements to teaching and learning. Journal of Educational Psychology. 2025;117(1):1.

About the Corresponding Author

Pandya Kruti Kumari Prakash Bhai is associated with Krishna School of Engineering and Technology, Drs. Kiran and Pallavi Patel Global University, Vadodara, Gujarat, India. Her academic interests include engineering studies, innovative technologies, and interdisciplinary research. She is actively involved in academic learning and research activities, contributing to technological and educational development.

Dr. Manisha Maulik Vaghela is a faculty member at Krishna School of Engineering and Technology, Drs. Kiran and Pallavi Patel Global University, Vadodara, Gujarat, India. She is engaged in teaching, research, and academic mentorship. Her areas of interest include engineering innovation, applied research, and the advancement of technical education through interdisciplinary approaches.