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Design and Evaluation of an Artificial Intelligence–Based Model for Predicting Twelfth-Grade Students' Mathematics Performance Based on Individual, Educational, and Learning Technology Factors

Najmeh. Yosefi[1], Mahdi. Azhini[1*], Hamidreza. Kashefi[2], Nourooz. Hashemi[2]

[1] Department of Mathematics, SR.C., Islamic Azad University, Tehran, Iran
[2] Department of Mathematics Education, Farhangian University, Tehran, Iran

*** Corresponding author email address**: azhini@iau.ir

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A B S T R A C T

Purpose: This study aimed to design and evaluate an artificial intelligence–based model for predicting the mathematics performance of twelfth-grade experimental sciences students based on individual, educational, and learning technology factors.
Methods and Materials: This applied, quantitative, cross-sectional, and predictive study was conducted among twelfth-grade experimental sciences students in Isfahan, Iran. A total of 187 questionnaires were distributed, and after removing incomplete, inconsistent, and invalid records, data from 84 students were retained for analysis. Data were collected using a structured questionnaire assessing individual factors, educational conditions, and learning technology variables, together with students' recorded mathematics scores. The dataset was divided into training and testing subsets, and repeated five-fold cross-validation was used for internal model development. Multiple linear regression, ridge regression, lasso regression, elastic net regression, decision tree regression, random forest regression, gradient boosting regression, and support vector regression were compared. Model performance was evaluated using mean absolute error, root mean squared error, and the coefficient of determination.
Findings: Previous mathematics achievement had the strongest positive correlation with current mathematics performance, followed by mathematics self-efficacy, study regularity, academic motivation, teacher feedback, instructional quality, and educational use of learning technologies. Test anxiety and digital distraction were negatively associated with mathematics performance. Among the evaluated algorithms, gradient boosting regression achieved the best predictive performance, with a test-set mean absolute error of 0.93, root mean squared error of 1.26, and coefficient of determination of .72. Previous mathematics achievement, mathematics self-efficacy, study regularity, teacher feedback, educational use of learning technologies, test anxiety, and instructional quality were the most influential predictors. Adding educational factors increased explained variance from .54 to .65, while including learning technology factors further increased it to .72.
Conclusion: The findings indicate that mathematics performance can be predicted with acceptable accuracy by integrating students' prior achievement, psychological and behavioral characteristics, instructional experiences, and learning technology use within an interpretable artificial intelligence model.
Keywords: *Artificial intelligence, machine learning, mathematics performance, predictive modeling, twelfth-grade students, educational technology, self-efficacy, gradient boosting*

1. Introduction

Mathematics achievement is a central indicator of educational quality because it reflects not only students' mastery of numerical and abstract concepts but also their capacity for logical reasoning, problem-solving, interpretation, and the application of knowledge in unfamiliar situations. Performance in mathematics during the final year of secondary education is especially consequential, as it can influence students' access to higher education, their selection of academic disciplines, and their readiness for university programs that require quantitative competence. Nevertheless, mathematics performance is not determined by a single cognitive or instructional factor. It emerges from the interaction of prior achievement, executive functioning, motivation, self-beliefs, anxiety, engagement, instructional opportunities, teacher practices, learning environments, and access to educational technologies. Recent evidence therefore supports a shift from simple, single-variable explanations toward multidimensional predictive frameworks capable of accounting for the complex and potentially nonlinear relationships among these factors (Niu et al., 2025; Zhu et al., 2025).

Traditional studies of mathematics achievement have commonly relied on correlation, regression, or group-comparison methods to identify variables associated with academic performance. Although these approaches remain valuable for estimating average relationships, they may be limited when predictors interact with one another, when associations are nonlinear, or when the relative importance of variables differs across student subgroups. Artificial intelligence and machine-learning methods provide an alternative analytical framework because they can process multiple heterogeneous predictors simultaneously, detect complex patterns, compare competing algorithms, and produce individual-level predictions. Ensemble tree-based approaches, neural networks, support vector machines, and regularized regression methods have increasingly been used in educational research to predict academic outcomes and identify the variables most strongly associated with students' performance. In a recent study using PISA 2022 data, ensemble tree-based machine-learning models generated predictive insights into mathematics performance and demonstrated the value of integrating multiple student and contextual characteristics rather than relying on a restricted set of conventional predictors (Zhu et al., 2025). Similarly, research on the early identification of mathematics difficulties showed that neural-network models can combine developmental and educational indicators to detect students at risk with a level of flexibility that is difficult to achieve through single-threshold screening methods (Psyridou et al., 2024).

The need for multidimensional modeling is further supported by evidence that mathematics performance is influenced by factors operating at different levels. These include characteristics located within the student, features of the classroom and teacher, family and peer support, school opportunities, and broader learning conditions. A multilevel analysis of student mathematics performance showed that individual and contextual variables jointly contribute to academic outcomes and that a comprehensive account of achievement requires attention to predictors located across several layers of the educational system (Niu et al., 2025). This perspective is important because apparently similar students may perform differently when exposed to different teaching practices, levels of feedback, technological resources, or opportunities to learn. Conversely, students in the same classroom may demonstrate markedly different outcomes because of differences in prior achievement, self-regulation, confidence, anxiety, cognitive functioning, and engagement. A predictive model that incorporates individual, educational, and learning-technology factors may therefore offer a more realistic representation of mathematics achievement than models constructed from a single category of variables.

Among individual predictors, prior academic achievement is generally one of the strongest indicators of subsequent performance because it reflects accumulated knowledge, earlier learning opportunities, and the degree to which prerequisite concepts have been mastered. However, previous achievement does not fully explain later outcomes. Cognitive executive functions, such as working memory, attentional control, inhibition, planning, and cognitive flexibility, also shape students' capacity to process mathematical information, maintain task goals, regulate problem-solving steps, and resist distraction. A principal component analysis of cognitive executive functions showed that these abilities can be organized into meaningful predictive dimensions associated with secondary school students' mathematics performance (Akpan et al., 2024). The implication is that prediction should not be restricted to grades alone, because two students with similar prior scores may differ in the cognitive resources needed to sustain performance in demanding mathematical tasks.

Metacognition represents another important individual factor. Students who can plan their learning, monitor

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comprehension, evaluate solution strategies, detect errors, and modify ineffective approaches are more likely to manage complex mathematics tasks successfully. Research examining metacognitive domains among senior high school students found that these domains possessed both correlational and predictive relationships with mathematics performance (Catador, 2024). Metacognition is closely related to self-regulated learning, which includes goal-setting, strategic planning, time management, self-monitoring, effort regulation, and self-evaluation. A review of the relationship between self-regulated learning and mathematics performance concluded that the major components of self-regulation are consistently connected with successful mathematics learning (Shaheema et al., 2023). These findings suggest that regular study, strategic learning behavior, and students' ability to organize their academic activities should be considered when designing predictive models.

Learning style and preferred modes of information processing may also affect how students engage with mathematical content. Although the concept of learning styles requires cautious interpretation, differences in students' approaches to receiving, organizing, and applying information may influence their participation and perceived compatibility with instructional methods. Research among Grade 8 students identified a relationship between mathematics performance and learning style, indicating that variation in learning preferences may be relevant when examining achievement patterns (Ocampo et al., 2023). At more advanced educational levels, structural equation modeling has also shown that mathematics-related academic performance is connected to a network of personal, academic, and environmental variables rather than a single isolated determinant (Wijaya et al., 2023). Accordingly, an artificial intelligence model may be particularly useful because it can estimate the relative contribution of multiple learning-related features while allowing for overlapping and conditional effects.

Mathematics self-efficacy is one of the most consistently supported psychological predictors of achievement. It refers to students' beliefs about their ability to understand mathematical concepts, complete assignments, solve problems, and perform successfully in examinations. Strong self-efficacy can encourage persistence, strategy use, task engagement, and resilience when students encounter difficulty, whereas weak self-efficacy can contribute to avoidance and premature disengagement. International evidence from PISA data showed that mathematics self-efficacy is closely connected with mathematics performance and that its relationship should be understood in conjunction with students' opportunities to learn (Wang et al., 2024). Self-efficacy may also operate together with interpersonal support. A study of alternative learning system students found that self-efficacy and peer support were associated with mathematics performance, suggesting that confidence is strengthened or weakened within a social environment rather than functioning as an entirely independent personal characteristic (Galamiton, 2025). These findings justify the inclusion of self-beliefs and supportive relationships in predictive analyses.

Student engagement is another multidimensional construct that includes behavioral participation, emotional involvement, cognitive investment, and agentic contribution to instruction. A systematic review and meta-analysis demonstrated that student engagement is positively associated with mathematics performance and subjective well-being, confirming that active involvement in learning is both an academic and psychological resource (Wong et al., 2024). Engagement is especially important in mathematics because students must repeatedly practice, explain reasoning, respond to feedback, and persist through errors. Emerging artificial intelligence–supported learning environments may also enhance agentic engagement by enabling students to exercise greater initiative and control over learning activities. Research on the use of Wordwall artificial intelligence reported improvements in students' agentic engagement and academic performance in mathematics, highlighting the possibility that digital tools can support achievement when they encourage active rather than passive participation (Allahkarami, 2025).

In contrast, test anxiety may impair mathematics performance by consuming attentional and working-memory resources, increasing intrusive thoughts, and disrupting the retrieval of learned procedures. The problem may become particularly pronounced in senior high school, where mathematics examinations have important educational consequences. Evidence from senior secondary students showed that test anxiety was negatively associated with academic performance in mathematics (Yarkwah et al., 2024). Anxiety may also be transmitted or amplified through instructional contexts. Teachers' own mathematics anxiety and mathematics teaching anxiety have been identified as predictors of students' mathematics performance, suggesting that emotional factors can enter the classroom through teacher behavior, communication, expectations, and instructional confidence (Awofala et al., 2024). Therefore,

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predictive models should consider both student-level anxiety and educational conditions that may intensify or reduce emotional barriers to learning.

Psychological strain more broadly can affect academic functioning by reducing concentration, motivation, persistence, and the capacity to regulate performance under pressure. Although research on psychological stress using deep-learning methods has been conducted in contexts beyond secondary mathematics, it demonstrates how artificial intelligence can be used to examine complex relationships between psychological states and student performance (Li, 2025). Such work is methodologically relevant because it shows that machine-learning algorithms can uncover patterns involving emotional and behavioral predictors that may not be adequately represented by linear assumptions. The broader application of artificial intelligence to performance prediction also reflects a growing interest in using computational models to interpret human behavior and outcomes in organizational and educational settings (Chen, 2024). Nevertheless, educational prediction differs from commercial or workplace performance modeling because it must remain interpretable, developmentally appropriate, and sensitive to the risks of labeling students on the basis of incomplete data.

Educational factors, particularly teacher practices, are also central to mathematics achievement. Teacher feedback can help students identify misconceptions, correct procedural errors, understand why an answer is inaccurate, and refine problem-solving strategies. Feedback is most effective when it is timely, specific, comprehensible, and directed toward improvement rather than judgment. Research analyzing the effect of teacher feedback found that it significantly influenced student performance in mathematics (Yalçın & Erdoğan, 2023). The quality of instruction may also depend on curriculum design, classroom management, teacher competence, and the alignment between learning objectives, activities, and assessment. A causal model of mathematics teachers' performance emphasized the interconnected roles of innovative curriculum design, classroom management strategies, and professional competencies (Dano & Prado, 2024). These findings indicate that student performance cannot be fully understood without examining the educational processes through which mathematical content is taught and practiced.

Active teaching methods may further improve motivation and achievement by involving students in games, projects, collaborative problem-solving, inquiry, and authentic applications of mathematics. Such methods can shift students from passive reception toward active construction of knowledge. Research on active approaches, including games and projects, has suggested positive effects on students' motivation and mathematics performance (Arefi, 2024). However, active teaching is not automatically effective. Its impact depends on instructional design, cognitive demand, teacher guidance, opportunities for reflection, and alignment with assessment. This complexity supports the use of predictive models that can examine instructional variables together rather than assuming that any single method produces uniform effects for all students.

Assessment practices also shape mathematics learning because they influence what students study, how they prepare, and the type of feedback they receive. Tailored testing can adapt item difficulty and content to students' performance levels, potentially generating more accurate information while supporting individualized learning. Research on tailored assessment among senior secondary mathematics students reported a positive effect on achievement (Omale, 2024). Process-based assessment can also capture how students construct solutions rather than focusing exclusively on final answers. Work involving GeoGebra showed that technology-supported process assessment can provide detailed information about students' mathematical performance, particularly in tasks involving quadratic curves (Oh, 2024). These approaches demonstrate that both assessment and prediction are moving toward richer, more individualized representations of learning.

The rapid development of educational technology has introduced additional predictors of mathematics performance. Digital learning resources can provide visualizations, immediate feedback, adaptive practice, interactive exercises, simulations, and repeated opportunities to apply concepts. Interactive mathematics software has been shown to improve learners' performance by supporting dynamic representation and active exploration of mathematical relationships (Uwineza et al., 2023). Tablet-based digital games have also been examined as tools for improving mathematics learning performance by combining practice with feedback, challenge, and engagement (Tepho & Srisawasdi, 2023). In mobile learning environments, adaptive game-based learning has produced improvements in mathematics performance among students with learning disabilities, indicating that personalization and responsiveness may be especially valuable for learners who require differentiated support (Samavati et al., 2024). These findings suggest that learning technology can contribute to

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mathematics achievement when it is pedagogically purposeful and appropriately matched to student needs.

At the same time, technology access should not be treated as equivalent to educationally effective use. Students may possess smartphones, computers, and internet access without using them for sustained mathematical learning. Digital devices can support instruction, but they can also generate distraction, multitasking, fragmented attention, and dependence on superficial answers. The influence of technology is therefore likely to depend on frequency of academic use, digital competence, self-regulation, perceived usefulness, instructional integration, and the balance between educational and non-educational activities. A predictive model should distinguish between mere access and productive utilization. It should also be capable of identifying interactions, such as whether technology use is more beneficial among students with stronger self-regulation or whether its positive contribution is reduced when digital distraction is high. Another important development is the use of interpretable artificial intelligence to examine disparities in mathematics performance. Predictive accuracy alone is insufficient when the goal is educational decision-making, because teachers and policymakers need to understand why a model generates a particular prediction and which factors are potentially modifiable. An interpretability-based examination of mathematics disparities demonstrated how artificial intelligence can identify influential features and reveal heterogeneous patterns underlying performance differences (Gomez-Talal et al., 2024). Interpretability is particularly important in school contexts because opaque predictions may reinforce existing inequalities if they rely heavily on socioeconomic, demographic, or institutional variables without clarifying their meaning. Explainable models can instead show whether predicted performance is associated with prior achievement, confidence, anxiety, feedback, instructional opportunity, purposeful technology use, or other actionable characteristics.

This research gap is important in the Iranian educational context. Twelfth-grade students face demanding mathematics curricula and high-stakes examinations during a transitional period that can determine access to university fields and future occupational pathways. Existing prediction models developed from international databases or different grade levels may not transfer directly to students in Isfahan because educational systems differ in curriculum structure, assessment, instructional practices, technology access, school environments, and sociocultural expectations. Furthermore, a locally developed model can provide more contextually relevant evidence about which factors are most influential and whether technological variables add predictive value beyond individual and educational characteristics.

Accordingly, the aim of this study was to design and evaluate an artificial intelligence–based model for predicting the mathematics performance of twelfth-grade experimental sciences students in Isfahan based on individual, educational, and learning technology factors.

2. Methods and Materials

2.1. Study Design and Participants

This study employed an applied, quantitative, cross-sectional, and predictive research design. The primary purpose was to design and evaluate an artificial intelligence–based model capable of predicting the mathematics performance of twelfth-grade students by simultaneously examining individual characteristics, educational conditions, and factors related to the use of learning technologies. The study was conducted in Isfahan, Iran, and the statistical population consisted of all twelfth-grade students enrolled in the experimental sciences track during the academic year in which the research was implemented. This population was selected because mathematics constitutes an important component of the experimental sciences curriculum and students' performance in this subject may be influenced by a complex combination of cognitive, motivational, instructional, environmental, and technological factors. The unit of analysis was the individual student, and participation in the study was voluntary. Students were informed of the general objectives of the research, the confidentiality of their information, and their right to withdraw from participation at any stage without any academic consequences.

To collect the required data, 187 questionnaires were distributed among eligible twelfth-grade students from selected upper secondary schools in Isfahan. The questionnaires were administered in coordination with school authorities and teachers and were completed either during designated school periods or through a supervised electronic data-collection procedure. Before the analysis, the collected data were subjected to a systematic screening process. Questionnaires with substantial missing data, internally inconsistent responses, repetitive response patterns, implausible values, or insufficient information on the outcome variable were excluded. Cases in which

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students had not provided reliable information regarding their mathematics performance or had left a considerable proportion of the questionnaire unanswered were also removed. This data-cleaning procedure was undertaken to reduce measurement error and ensure that the artificial intelligence model was trained using complete, coherent, and valid observations. Following the initial assessment and removal of incomplete, inconsistent, or invalid records, the data of 84 students were identified as complete and analytically usable and were included in the final analysis.

The eligibility criteria required participants to be enrolled in the twelfth grade of the experimental sciences track in a secondary school located in Isfahan, to have attended mathematics courses during the study period, to possess an available and verifiable indicator of mathematics performance, and to provide informed consent to participate. Students were excluded when they submitted incomplete questionnaires, provided contradictory or evidently unreliable responses, lacked valid mathematics achievement data, or withdrew from the study. No personally identifying information was included in the analytical dataset. Each participant was assigned a numerical code, and the database used for model development contained only the variables required for statistical analysis and machine-learning prediction. The final sample was used to investigate the predictive contribution of individual, educational, and learning technology variables and to develop a model that could estimate students' mathematics performance with an acceptable level of accuracy.

2.2. Data Collection Tools

Data were collected using a structured questionnaire developed according to the conceptual framework of the study and a mathematics performance record form. The questionnaire was designed to capture three major groups of predictor variables, including individual factors, educational factors, and factors related to learning technologies. The selection of variables was guided by theoretical considerations regarding academic achievement and by the assumption that mathematics performance is a multidimensional outcome that cannot be adequately predicted through demographic or academic variables alone. Accordingly, the questionnaire incorporated variables reflecting students' personal characteristics, learning-related attitudes and behaviors, instructional experiences, family and school support, and access to and use of digital learning resources.

The individual factors section collected basic demographic and personal information, including age, gender, previous academic achievement, study habits, average daily study time, class attendance, mathematics self-efficacy, academic motivation, test anxiety, concentration during learning activities, perceived difficulty of mathematics, and interest in the subject. Mathematics self-efficacy referred to the student's perceived ability to understand mathematical concepts, solve mathematical problems, complete assignments, and perform successfully in examinations. Academic motivation reflected the extent to which students were willing to invest effort, persist in difficult tasks, and achieve desirable educational outcomes. Test anxiety covered students' cognitive and emotional reactions before and during mathematics assessments, while study habits included planning, regularity of practice, review of lessons, completion of homework, and persistence when encountering complex problems. These variables were measured using clear statements rated on a five-point Likert scale ranging from strongly disagree to strongly agree. Negatively worded items were reverse-scored so that higher scores consistently represented higher levels of the relevant construct, except in variables such as anxiety and perceived difficulty, for which higher scores indicated a greater level of the measured problem.

The educational factors section assessed the instructional and contextual conditions associated with mathematics learning. The variables included perceived quality of mathematics instruction, clarity of teachers' explanations, teacher feedback, teacher support, opportunity to ask questions, frequency of formative assessment, quality and quantity of homework, classroom participation, perceived classroom climate, availability of supplementary instruction, parental academic support, peer support, access to educational resources, and satisfaction with school-based mathematics instruction. Teacher-related items examined the extent to which the mathematics teacher presented concepts in an understandable manner, used diverse teaching strategies, provided examples, corrected students' errors, encouraged active participation, and adapted instruction to learners' needs. Classroom-related variables addressed students' perceptions of order, psychological safety, interaction, competition, cooperation, and the suitability of the learning environment. Family-related items focused on parental encouragement, monitoring of academic progress, provision of learning resources, and assistance in organizing study time. Responses to these items were also recorded on a five-point Likert scale.

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The learning technology section measured students' access to, frequency of use of, and perceived effectiveness of technology-assisted learning resources. This section included access to smartphones, tablets, computers, and stable internet connections; frequency of using educational websites, video-based lessons, online practice platforms, learning management systems, digital textbooks, mathematics applications, artificial intelligence–assisted educational tools, online communication with teachers, and virtual study groups; and the extent to which students used technology for explanation, practice, feedback, problem-solving, review, and preparation for examinations. Additional items evaluated students' digital competence, ability to assess the reliability of online educational content, perceived ease of using learning technologies, perceived usefulness of digital resources, engagement in technology-supported learning, and possible distractions caused by excessive or non-academic use of digital devices. The inclusion of both beneficial and potentially disruptive aspects of technology use made it possible to distinguish purposeful educational use from general screen exposure.

The dependent variable was students' mathematics performance. This variable was determined using the most recent available mathematics score recorded in the students' academic records, preferably the final or standardized mathematics examination score corresponding to the twelfth-grade curriculum. When necessary, the reported score was checked against school records to minimize self-report bias. Mathematics scores were standardized to a common scale before model development when different scoring formats were encountered. The continuous mathematics score was used as the primary outcome variable because it preserved the full variability of students' achievement and allowed the artificial intelligence algorithms to be evaluated as regression models. For supplementary interpretation, performance scores could also be classified into lower, moderate, and higher achievement levels based on the distribution of scores; however, the primary model was designed to predict the continuous mathematics performance score.

The initial questionnaire was reviewed for content relevance, clarity, comprehensiveness, and correspondence with the objectives of the study. Specialists in educational psychology, mathematics education, educational technology, measurement and evaluation, and artificial intelligence were asked to examine the items and assess whether the instrument adequately covered the proposed predictor domains. Items considered ambiguous, repetitive, or weakly related to mathematics performance were revised or removed. A preliminary administration was conducted with a small group of students who were comparable to the target population but were not included in the final analysis. Their feedback was used to improve the wording, readability, and completion time of the questionnaire. The internal consistency of multi-item constructs was assessed before the predictive analysis, and composite scores were calculated only when the items demonstrated an acceptable level of coherence. Higher composite scores represented greater levels of the corresponding individual, educational, or technology-related characteristic.

2.3. Data Analysis

Data analysis was performed in several consecutive stages, including data preparation, descriptive analysis, feature processing, artificial intelligence model development, performance evaluation, and interpretation of predictor importance. Initially, all questionnaire responses and mathematics performance scores were entered into a unified dataset. The accuracy of data entry was checked, duplicate records were removed, and the range and distribution of each variable were examined. Invalid values, logically inconsistent responses, and cases with extensive missing information had already been excluded during the screening stage. For variables with a very small proportion of missing values, appropriate imputation procedures were considered according to the measurement level and distribution of the variable. Numerical missing values were replaced using a robust central estimate derived from the training data, whereas categorical missing values were handled using the most frequent valid category. To prevent information leakage, all preprocessing parameters were estimated exclusively from the training portion of the data and subsequently applied to the evaluation portion.

Descriptive statistics were calculated to summarize the characteristics of the participants and the study variables. Means, standard deviations, minimums, maximums, medians, and interquartile ranges were used for continuous variables, while frequencies and percentages were calculated for categorical variables. The distributions of mathematics performance and the principal predictor variables were examined to identify skewness, extreme values, restricted variability, and possible data-entry errors. Correlation coefficients were calculated as an initial exploratory procedure to evaluate the direction and magnitude of relationships between numerical predictors and mathematics

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performance. These conventional analyses were used for descriptive and diagnostic purposes and did not replace the multivariable artificial intelligence modeling procedure.

Before model training, categorical variables were transformed into machine-readable numerical representations using appropriate encoding techniques. Binary variables were coded as zero and one, while nominal variables with more than two categories were represented using one-hot encoding. Continuous variables were standardized when the algorithm was sensitive to differences in measurement scales. Standardization transformed each numerical variable using the mean and standard deviation calculated from the training data. Variables with near-zero variance were removed because they contributed little useful information to prediction. Highly redundant variables were identified through correlation analysis and conceptual review. When two variables contained almost identical information, the more interpretable or theoretically relevant variable was retained to reduce unnecessary model complexity.

The final dataset was divided into training and testing subsets. Because the number of complete observations was relatively limited, the training set was used for model fitting and internal optimization, while the testing set was reserved for evaluating predictive performance on data not used during model construction. The division was performed randomly while preserving, as far as possible, the distribution of mathematics performance across the two subsets. To obtain a more stable estimate of performance and reduce the dependence of findings on a single random partition, repeated k-fold cross-validation was employed within the training data. In this procedure, the training observations were divided into several folds, the model was repeatedly trained on all but one fold, and performance was assessed on the remaining fold. This process was repeated until every fold had served as the validation set. Model hyperparameters were selected according to the average cross-validation performance rather than performance on the final test set.

Several supervised machine-learning algorithms were examined to determine which approach provided the most accurate and generalizable prediction of mathematics performance. A multiple linear regression model was first fitted as an interpretable baseline. Regularized regression models, including ridge regression, lasso regression, and elastic net regression, were then evaluated to control model complexity and reduce the effects of multicollinearity. Tree-based algorithms were also examined because they can capture nonlinear associations and interactions among individual, educational, and technological variables. These algorithms included a decision tree regressor, random forest regressor, and gradient boosting regressor. A support vector regression model was considered to model complex patterns through kernel-based transformations. The algorithms were trained using the same cross-validation structure so that their predictive performance could be compared under equivalent conditions.

Hyperparameter tuning was conducted within the training data. For regularized regression models, the strength of the penalty and the balance between lasso and ridge penalties were optimized. For decision tree and ensemble models, parameters such as maximum tree depth, minimum number of observations required for splitting, minimum number of observations in terminal nodes, number of trees, number of variables considered at each split, learning rate, and number of boosting iterations were evaluated. For support vector regression, the penalty parameter, kernel coefficient, and insensitive loss margin were optimized. The search procedure was restricted to plausible parameter ranges to reduce the risk of overfitting, which was particularly important because the final analytical sample included 84 students. The model with the best cross-validated predictive performance and acceptable stability was selected as the final artificial intelligence model.

Feature selection was incorporated into the modeling process to identify the most informative predictors and reduce unnecessary dimensionality. The first stage involved removing variables with minimal variance, excessive redundancy, or insufficient valid responses. The second stage used algorithm-specific procedures, including regularization coefficients, recursive feature elimination, permutation-based importance, and tree-based feature importance. Feature selection was performed within the cross-validation process rather than on the complete dataset to avoid optimistic bias. The final set of predictors was chosen by considering predictive contribution, stability across validation folds, theoretical relevance, and interpretability. This approach was intended to ensure that the final model was not only accurate but also educationally meaningful.

Model performance was evaluated using several complementary regression metrics. The mean absolute error represented the average absolute difference between predicted and observed mathematics scores and provided an easily interpretable estimate of prediction error. The root mean squared error assigned greater weight to larger errors

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and was used to identify models that produced occasional substantial inaccuracies. The coefficient of determination indicated the proportion of variance in mathematics performance explained by the model. The mean squared error was also calculated for optimization and model comparison. These indices were first estimated through cross-validation within the training set and were then calculated on the independent test set. A model was considered superior when it demonstrated lower mean absolute error and root mean squared error, a higher coefficient of determination, and a limited difference between training and testing performance.

The possibility of overfitting was assessed by comparing model performance across the training, validation, and testing stages. A substantial decline in test performance relative to training performance was interpreted as evidence that the model had learned sample-specific noise rather than generalizable patterns. To control this problem, model complexity was constrained, regularization was applied, cross-validation was used, and overly complex predictor sets were avoided. Residuals were examined to determine whether prediction errors were systematically related to actual performance levels. Particular attention was given to whether the model produced larger errors for students with very low or very high mathematics scores, because such patterns could reduce its practical usefulness.

After selecting the final model, predictor importance was examined to determine which individual, educational, and learning technology variables contributed most strongly to the prediction of mathematics performance. For linear and regularized models, standardized regression coefficients were examined. For tree-based models, permutation importance was used because it measures the decline in predictive accuracy after the values of a predictor are randomly rearranged. Model-agnostic interpretability procedures were also employed to clarify the direction and magnitude of influential variables. These procedures indicated whether higher values of a predictor tended to increase or decrease the predicted mathematics score and whether the association appeared linear or nonlinear. The interpretation of variable importance was conducted cautiously because predictive importance does not necessarily establish a causal relationship.

To assess the added value of learning technology factors, hierarchical groups of predictors were compared. A model containing only individual factors was first evaluated, followed by a model combining individual and educational variables. The third model included individual, educational, and learning technology factors simultaneously. Improvements in cross-validated error indices and the coefficient of determination were examined to determine whether technology-related variables contributed meaningful predictive information beyond students' personal characteristics and educational conditions. This comparison directly addressed the multidimensional framework of the study and made it possible to determine whether the inclusion of digital learning variables enhanced the prediction of mathematics achievement.

All analyses were conducted using statistical and machine-learning software capable of data preprocessing, cross-validation, hyperparameter optimization, predictive modeling, and model interpretation. A fixed random seed was applied to improve the reproducibility of data partitioning and model estimation. Statistical tests, where used for descriptive or preliminary analyses, were interpreted at a significance level of .05. However, selection of the final predictive model was based primarily on out-of-sample prediction metrics rather than statistical significance alone. The complete analytical process was designed to maximize data quality, minimize information leakage and overfitting, and produce an interpretable artificial intelligence model suitable for predicting the mathematics performance of twelfth-grade students on the basis of individual, educational, and learning technology factors.

3. Findings and Results

The final analytical sample consisted of 84 twelfth-grade students enrolled in the experimental sciences track in secondary schools in Isfahan. The participants' mean age was 17.72 years (SD = 0.46), with ages ranging from 17 to 19 years. Of the participants, 46 students (54.8%) were female and 38 students (45.2%) were male. A total of 58 students (69.0%) attended public schools, whereas 26 students (31.0%) attended non-public schools. Regarding parental educational attainment, 21 students (25.0%) reported that neither parent held a university degree, 37 students (44.0%) reported that one parent held a university degree, and 26 students (31.0%) reported that both parents had completed university education. In terms of access to digital learning resources, 79 students (94.0%) reported access to a smartphone, 63 students (75.0%) had access to a personal or shared computer or tablet, and 71 students (84.5%) reported having relatively stable home internet access. Fifty-nine students (70.2%) stated that they used digital learning resources for mathematics at least three

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times per week, while 25 students (29.8%) reported less frequent use. The students' previous-year grade point average ranged from 12.60 to 19.86, with a mean of 17.08 (SD = 1.58). The mean observed mathematics performance score in the twelfth grade was 15.42 out of 20 (SD = 2.36), indicating that the final sample included students with a relatively broad range of mathematics achievement.

Table 1

Descriptive Statistics for Mathematics Performance and the Principal Predictor Variables

Variable	Possible range	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis
Mathematics performance	0–20	9.25	19.50	15.42	2.36	−0.42	−0.51
Previous mathematics achievement	0–20	8.75	19.75	15.87	2.41	−0.48	−0.39
Mathematics self-efficacy	1–5	1.80	4.90	3.61	0.72	−0.29	−0.44
Academic motivation	1–5	2.00	4.93	3.72	0.65	−0.34	−0.21
Test anxiety	1–5	1.47	4.80	3.09	0.76	0.11	−0.38
Study regularity	1–5	1.67	5.00	3.54	0.71	−0.18	−0.31
Daily mathematics study time	0–4 hours	0.25	3.75	1.64	0.79	0.57	−0.12
Perceived instructional quality	1–5	1.73	4.93	3.68	0.66	−0.35	−0.19
Teacher feedback and support	1–5	1.67	5.00	3.74	0.70	−0.41	−0.08
Classroom participation	1–5	1.60	4.87	3.49	0.68	−0.12	−0.36
Parental academic support	1–5	1.80	5.00	3.76	0.73	−0.46	−0.17
Access to digital learning resources	1–5	1.75	5.00	4.01	0.69	−0.62	0.18
Educational use of learning technologies	1–5	1.44	4.89	3.57	0.72	−0.23	−0.41
Digital learning competence	1–5	1.67	5.00	3.83	0.67	−0.39	−0.13
Perceived usefulness of learning technologies	1–5	1.50	5.00	3.79	0.74	−0.44	−0.28
Digital distraction	1–5	1.20	4.80	2.94	0.81	0.19	−0.46

As shown in Table 1, the students' mathematics performance scores demonstrated sufficient variability for predictive modeling, with observed scores ranging from 9.25 to 19.50. The mean mathematics score of 15.42 suggested generally moderate-to-high achievement, although the standard deviation of 2.36 indicated meaningful differences among students. Previous mathematics achievement had a mean of 15.87 and displayed a distribution similar to that of the outcome variable. Among the individual predictors, academic motivation, mathematics self-efficacy, and study regularity showed mean values above the theoretical midpoint of the five-point scale, whereas test anxiety was close to the midpoint. The mean daily mathematics study time was 1.64 hours, but the relatively large standard deviation indicated considerable differences in students' study duration. Among the educational factors, teacher feedback and support, perceived instructional quality, and parental academic support received relatively high mean scores. Access to digital learning resources had the highest mean among the technology-related variables, suggesting that most participants had adequate access to digital devices and internet-based educational materials. However, the mean score for educational use of learning technologies was lower than the mean access score, indicating that access to technology did not necessarily translate into frequent or purposeful academic use. Digital distraction had a mean of 2.94, showing that non-academic or disruptive use of digital devices was present at a moderate level. The absolute values of skewness and kurtosis were below 1.00 for all variables, indicating that none of the distributions exhibited severe departure from normality. These findings supported the suitability of the variables for preliminary correlational analysis and for inclusion in the subsequent machine-learning procedures.

Table 2

Correlations Between the Principal Predictor Variables and Mathematics Performance

Predictor variable	Correlation with mathematics performance	p-value
Previous mathematics achievement	.71	< .001
Mathematics self-efficacy	.64	< .001
Academic motivation	.52	< .001
Test anxiety	−.46	< .001

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Study regularity	.55	< .001
Daily mathematics study time	.38	< .001
Perceived instructional quality	.49	< .001
Teacher feedback and support	.51	< .001
Classroom participation	.43	< .001
Parental academic support	.36	.001
Access to digital learning resources	.24	.030
Educational use of learning technologies	.47	< .001
Digital learning competence	.41	< .001
Perceived usefulness of learning technologies	.35	.001
Digital distraction	−.39	< .001

The correlation coefficients presented in Table 2 indicated that mathematics performance was significantly associated with variables from all three predictor domains. Previous mathematics achievement had the strongest bivariate relationship with current mathematics performance, r = .71, p < .001, demonstrating substantial continuity between earlier and current academic achievement. Mathematics self-efficacy also had a strong positive relationship with performance, r = .64, p < .001, indicating that students who expressed greater confidence in their ability to understand mathematical concepts and solve mathematical problems generally obtained higher mathematics scores. Study regularity, academic motivation, teacher feedback and support, and perceived instructional quality showed moderate positive correlations with mathematics performance. These findings suggested that both students' learning-related characteristics and the quality of their instructional experiences were relevant to their academic outcomes. Test anxiety was negatively related to mathematics performance, r = −.46, p < .001, indicating that students who experienced greater anxiety during mathematics assessments tended to achieve lower scores. Among the technology-related variables, educational use of learning technologies demonstrated the strongest positive correlation with mathematics performance, r = .47, p < .001. Digital learning competence and perceived usefulness of learning technologies were also positively associated with performance. Access to technology had a weaker correlation, r = .24, p = .030, showing that merely possessing digital resources was less strongly related to achievement than using those resources effectively for educational purposes. Digital distraction was negatively related to mathematics performance, r = −.39, p < .001, suggesting that unfocused or non-academic use of digital devices may interfere with mathematics learning. The correlations were not sufficiently high to indicate complete redundancy among the predictors, and their differing magnitudes supported the inclusion of multiple individual, educational, and technological variables in the predictive models. The 84 complete cases were randomly divided into a training subset containing 67 students, equivalent to 79.8% of the sample, and a testing subset containing 17 students, equivalent to 20.2% of the sample. The mean mathematics score was 15.39 (SD = 2.39) in the training subset and 15.53 (SD = 2.31) in the testing subset. The difference between the two subsets was not statistically significant, indicating that the random partition maintained a comparable distribution of the outcome variable. Hyperparameter selection and feature selection were conducted within the training subset through repeated five-fold cross-validation. Seven predictive algorithms were compared using the same resampling structure. Model performance was primarily assessed through the mean absolute error, root mean squared error, and coefficient of determination.

Table 3

Cross-Validated and Test-Set Performance of the Predictive Models

Predictive model	Cross-validated MAE	Cross-validated RMSE	Cross-validated R^2	Test MAE	Test RMSE	Test R^2
Multiple linear regression	1.31	1.69	.49	1.37	1.75	.46
Ridge regression	1.18	1.52	.58	1.22	1.57	.56
Lasso regression	1.20	1.55	.56	1.25	1.61	.53
Elastic net regression	1.14	1.48	.60	1.19	1.53	.59
Decision tree regression	1.42	1.83	.42	1.48	1.91	.35
Random forest regression	1.00	1.34	.68	1.04	1.38	.67
Gradient boosting regression	0.91	1.20	.74	0.93	1.26	.72
Support vector regression	1.07	1.40	.65	1.10	1.44	.64

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The results presented in Table 3 demonstrated that the gradient boosting regression model produced the most accurate predictions. During repeated cross-validation, this model achieved a mean absolute error of 0.91, a root mean squared error of 1.20, and a coefficient of determination of .74. Its performance remained stable when applied to the independent testing subset, with a mean absolute error of 0.93 and a root mean squared error of 1.26. The test-set R^2 of .72 indicated that the final model explained approximately 72% of the variance in mathematics performance among students who had not been used in model training. The small difference between the cross-validated and test-set performance suggested limited overfitting and acceptable generalizability within the boundaries of the sample. The random forest model ranked second, explaining 67% of the variance in the test subset, followed by support vector regression, which explained 64% of the variance. Elastic net regression outperformed ordinary multiple regression and the separate ridge and lasso models, suggesting that regularization improved prediction by reducing the adverse effects of redundant or weak predictors. The single decision tree produced the poorest performance, with a test-set R^2 of .35 and a root mean squared error of 1.91. This result indicated that a single hierarchical partition of the data was insufficient to capture the complex relationships among individual, educational, technological, and performance-related variables. In contrast, ensemble methods, particularly gradient boosting, were better able to model nonlinear relationships and conditional interactions. On average, the gradient boosting model's predicted mathematics score differed from the observed score by less than one point on the 20-point scale, which represented a practically meaningful level of predictive accuracy.

The optimized gradient boosting model consisted of 150 sequentially fitted trees, a learning rate of 0.05, a maximum tree depth of three, and a minimum terminal-node size of four observations. The relatively shallow tree depth and low learning rate were selected through cross-validation and helped limit model complexity. The final feature-selection procedure retained 12 predictors from the original set of individual, educational, and learning technology variables. Variables that demonstrated unstable or negligible contributions across validation folds were removed. Permutation importance and model-agnostic contribution values were then used to determine the relative contribution and direction of each retained predictor.

Table 4

Relative Importance and Direction of Predictors in the Final Gradient Boosting Model

Rank	Predictor	Predictor domain	Relative importance (%)	Predominant direction of association
1	Previous mathematics achievement	Individual/academic history	23.4	Positive
2	Mathematics self-efficacy	Individual	15.8	Positive
3	Study regularity	Individual	10.7	Positive
4	Teacher feedback and support	Educational	9.4	Positive
5	Educational use of learning technologies	Learning technology	8.8	Positive
6	Test anxiety	Individual	7.9	Negative
7	Perceived instructional quality	Educational	6.8	Positive
8	Digital distraction	Learning technology	5.9	Negative
9	Academic motivation	Individual	4.8	Positive
10	Digital learning competence	Learning technology	3.2	Positive
11	Classroom participation	Educational	1.9	Positive
12	Parental academic support	Educational	1.4	Positive

Table 4 shows that previous mathematics achievement was the most influential predictor in the final model, accounting for 23.4% of the total permutation-based importance. Higher previous mathematics scores consistently increased predicted twelfth-grade mathematics performance, although the contribution was not completely linear. The model showed that the predictive benefit associated with previous performance was particularly pronounced among students whose earlier scores were in the middle and upper ranges. Mathematics self-efficacy was the second most influential predictor, with a relative importance of 15.8%. Students with higher confidence in their ability to understand and solve mathematics problems generally received higher predicted scores, even after prior performance and instructional variables were considered. Study regularity ranked third, indicating that consistent study patterns were more informative than the total amount of study time alone. Teacher feedback and support was the

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most important educational variable, suggesting that timely correction, explanatory feedback, and opportunities to resolve learning difficulties contributed meaningfully to the model's predictions. Educational use of learning technologies was the most important technology-related predictor. Purposeful use of videos, online exercises, mathematics applications, digital feedback systems, and virtual educational resources was associated with higher predicted performance. Test anxiety and digital distraction had negative contributions, meaning that elevated levels of these variables reduced predicted mathematics scores. The importance of digital distraction, together with the positive contribution of educational technology use, indicated that the relationship between technology and achievement depended on the manner in which digital resources were used. Perceived instructional quality, academic motivation, digital competence, classroom participation, and parental support made smaller but stable contributions. The combined results showed that the final model did not depend exclusively on previous academic achievement and that modifiable psychological, instructional, and technological variables added meaningful predictive information.

To determine the incremental contribution of the three predictor domains, three nested gradient boosting models were compared. The first model was trained using only individual factors, including previous performance, mathematics self-efficacy, motivation, test anxiety, study regularity, and study time. The second model added educational factors, including instructional quality, teacher feedback, classroom participation, and parental support. The third and final model included individual, educational, and learning technology factors simultaneously.

Table 5

Incremental Predictive Performance of the Individual, Educational, and Learning Technology Domains

Model	Predictor domains included	Test MAE	Test RMSE	Test R^2	Increase in R^2
Model A	Individual factors	1.25	1.61	.54	—
Model B	Individual and educational factors	1.07	1.40	.65	.11
Model C	Individual, educational, and learning technology factors	0.93	1.26	.72	.07

As reported in Table 5, the model based exclusively on individual factors explained 54% of the variance in mathematics performance and produced a test-set root mean squared error of 1.61. Adding educational factors increased the explained variance to 65%, representing an improvement of 11 percentage points, while reducing the mean absolute error from 1.25 to 1.07. This improvement indicated that teacher-related and classroom-related variables contributed information that was not fully represented by students' personal characteristics or previous performance. When learning technology factors were added, the coefficient of determination increased from .65 to .72, and the root mean squared error decreased from 1.40 to 1.26. Thus, technology-related variables explained an additional 7% of performance variance beyond the individual and educational domains. The full model reduced the mean absolute prediction error by 0.32 points compared with the individual-only model. This improvement was attributable primarily to the educational use of learning technologies, digital learning competence, and digital distraction rather than to access to digital devices alone. The incremental analysis therefore supported the study's multidimensional framework and demonstrated that the most accurate prediction was achieved when personal, instructional, and technology-related information was integrated within a single model.

The graphical comparison of observed and predicted mathematics performance indicated that most cases were distributed close to the diagonal line representing perfect prediction. The model reproduced the general ranking of students from lower to higher achievement and did not show a systematic tendency to overestimate or underestimate scores across the central portion of the distribution. Prediction errors were smallest among students with observed mathematics scores between approximately 13 and 18, which represented the range containing most participants. Some compression was observed at the extremes, as the model slightly overestimated the performance of a small number of lower-achieving students and slightly underestimated the scores of a small number of very high-achieving students. Nevertheless, no extreme residuals were observed in the test subset. The mean residual was close to zero, and the distribution of residuals was approximately symmetrical. The correspondence between observed and predicted scores was also reflected in a strong test-set correlation of .86, indicating close agreement between actual performance and the scores generated by the artificial intelligence model. The graphical pattern was

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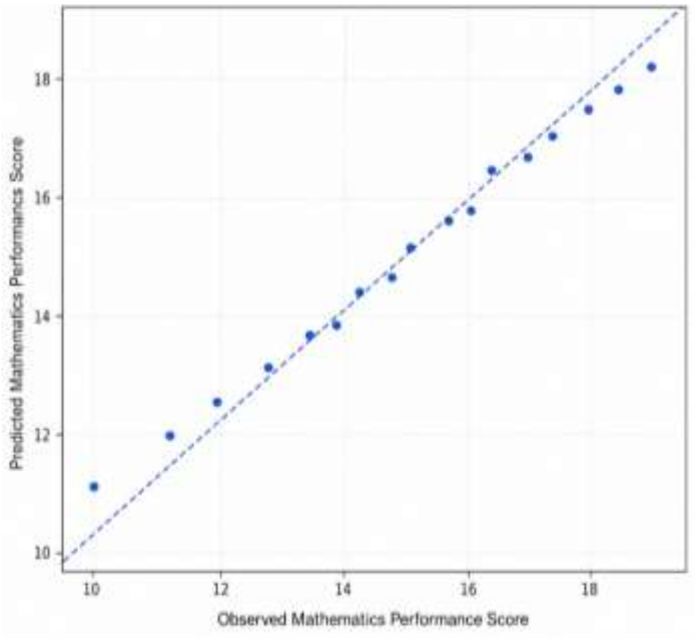
therefore consistent with the error indices reported for the gradient boosting model and supported its ability to distinguish among different levels of mathematics performance.

Further examination of the prediction errors showed that the mean residual, calculated as the observed score minus the predicted score, was 0.06, indicating negligible overall bias. The standard deviation of the residuals was 1.29, and 82.4% of the test-set predictions were within 1.50 points of the observed mathematics score. In addition, 94.1% of the predicted scores were within 2.00 points of the observed score. The largest absolute prediction error was 2.47 points and occurred for a student with a relatively low previous mathematics score, moderate self-efficacy, high test anxiety, and irregular use of educational technology. Residuals were not significantly correlated with predicted scores, indicating that the magnitude of the model's errors did not systematically increase across the predicted performance range. These results provided additional evidence that the final model achieved a reasonable balance between predictive accuracy and generalization.

Figure 1

Relationship Between Observed and Predicted Mathematics Performance Scores in the Test Dataset



The model interpretation analysis also revealed several nonlinear patterns. The positive effect of mathematics self-efficacy was most evident when self-efficacy scores increased from approximately 2.8 to 4.0, after which the marginal increase in predicted performance became smaller. This pattern indicated that moving from low or moderate self-efficacy to a relatively high level was more strongly associated with predicted achievement than movement within the already-high range. Study regularity displayed a similar threshold pattern, with a noticeable increase in predicted performance when students moved from irregular study practices to consistently scheduled study. Teacher feedback had a positive contribution across most of its range, but its effect was strongest among students with moderate previous achievement, suggesting that constructive feedback may be particularly informative for predicting the performance of students whose earlier scores do not clearly place them in either the high- or low-achievement group.

The effect of learning technology use was also conditional rather than uniform. Students who reported moderate-to-high purposeful use of online exercises, instructional videos, digital problem-solving tools, and immediate feedback resources generally had higher predicted scores. However, very high levels of general device use did not necessarily correspond to higher achievement. When high technology use was accompanied by high digital distraction, the predicted benefit was substantially reduced. Conversely, students with moderate device use but high educational purpose and strong digital competence received relatively favorable predictions. Access to digital resources had little independent influence after purposeful use and digital competence were included

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in the model. This finding suggested that the educational quality and self-regulation of technology use were more predictive than the mere availability of devices or internet access.

Interaction analysis indicated that mathematics self-efficacy moderated the predictive contribution of previous mathematics achievement. Students with similar previous mathematics scores received different predicted outcomes depending on their self-efficacy levels. Among students with moderate previous achievement, high self-efficacy was associated with substantially higher predicted performance than low self-efficacy. The interaction between teacher feedback and study regularity was also notable. Students who maintained regular study schedules appeared to benefit more strongly from teacher feedback, possibly because they were more likely to review, apply, and consolidate the information provided by the teacher. A further interaction was found between educational technology use and digital competence. Purposeful technology use had a stronger positive contribution among students with sufficient digital skills, whereas frequent use without adequate competence produced a smaller predictive benefit.

An examination of model performance across demographic subgroups did not indicate substantial instability. The mean absolute error was 0.91 among female students and 0.96 among male students. The difference was small and did not suggest that the model systematically performed better for one gender. The mean absolute error was 0.95 among public-school students and 0.89 among non-public-school students. Although prediction accuracy was marginally higher in non-public schools, the difference was limited and should be interpreted cautiously because of the smaller number of non-public-school participants. Prediction errors were also examined according to lower, middle, and upper categories of previous achievement. The model performed most accurately in the middle-achievement group, with a mean absolute error of 0.84. The corresponding errors were 1.07 in the lower-achievement group and 0.99 in the upper-achievement group. These results were consistent with the slight compression at the lower and upper ends of the performance distribution observed in Figure 1.

Overall, the findings demonstrated that mathematics performance could be predicted with relatively high accuracy by integrating students' previous achievement, psychological and behavioral characteristics, educational experiences, and patterns of learning technology use. Previous mathematics achievement remained the strongest individual predictor, but it did not fully determine current performance. Mathematics self-efficacy, regular study behavior, teacher feedback, instructional quality, test anxiety, purposeful use of learning technologies, and digital distraction contributed additional information. Ensemble-based artificial intelligence algorithms performed better than conventional linear regression and a single decision tree, with gradient boosting producing the lowest prediction errors and the highest explained variance. The final model explained 72% of the variance in the independent test data and generated predictions that differed from observed mathematics scores by an average of less than one point. These findings supported the use of a multidimensional artificial intelligence model for identifying patterns associated with the mathematics performance of twelfth-grade students.

4. Discussion and Conclusion

The present study designed and evaluated an artificial intelligence–based model for predicting the mathematics performance of twelfth-grade students in the experimental sciences track on the basis of individual, educational, and learning technology factors. The findings showed that mathematics performance was significantly associated with predictors from all three domains. Previous mathematics achievement had the strongest bivariate relationship with current performance, followed by mathematics self-efficacy, study regularity, academic motivation, teacher feedback and support, perceived instructional quality, educational use of learning technologies, and classroom participation. Test anxiety and digital distraction were negatively related to mathematics performance. Among the evaluated algorithms, gradient boosting regression demonstrated the strongest predictive performance, outperforming multiple linear regression, regularized regression, a single decision tree, random forest regression, and support vector regression. The final gradient boosting model explained 72% of the variance in mathematics scores in the test dataset and produced a mean absolute prediction error of less than one point on the 20-point mathematics scale. The incremental modeling analysis further showed that adding educational variables to individual predictors substantially improved the model and that the inclusion of learning technology factors generated an additional improvement in predictive accuracy.

The superior performance of the gradient boosting model supports the assumption that mathematics achievement is produced through complex, overlapping, and potentially

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nonlinear relationships among student characteristics and learning conditions. Conventional linear models assume that predictor effects are largely additive and stable across the full range of observations. In contrast, ensemble tree-based models can identify threshold effects, nonlinear associations, and interactions without requiring them to be specified in advance. The finding that gradient boosting outperformed ordinary regression is consistent with research showing that ensemble machine-learning methods can provide accurate and interpretable predictions of students' mathematics achievement when numerous personal and contextual variables are analyzed simultaneously (Zhu et al., 2025). It also agrees with evidence that artificial neural networks can integrate multiple early indicators and identify students at risk for mathematics difficulties more effectively than narrow screening approaches based on individual variables (Psyridou et al., 2024). The present findings therefore reinforce the methodological value of artificial intelligence for educational prediction, particularly when the target outcome is influenced by multiple levels of the learning environment.

Previous mathematics achievement emerged as the strongest predictor in both the correlational and machine-learning analyses. This result was expected because current mathematics performance depends considerably on the cumulative mastery of prerequisite concepts, procedural knowledge, and problem-solving strategies. Students who possess stronger mathematical foundations are more capable of understanding advanced material, connecting new information with prior knowledge, and completing complex tasks successfully. The prominence of prior achievement is consistent with multilevel research indicating that earlier academic competence remains one of the most stable student-level predictors of later mathematics outcomes, even when instructional and contextual variables are considered (Niu et al., 2025). However, the final model also showed that previous achievement did not completely determine current performance. Students with comparable earlier scores received different predictions depending on their self-efficacy, study regularity, anxiety, teacher support, and use of learning technologies. This finding is important because it suggests that mathematics performance is not fixed by academic history and that modifiable psychological and educational factors can meaningfully alter students' expected outcomes.

Mathematics self-efficacy was the second most important variable in the final model and had a strong positive correlation with mathematics achievement. Students who believed that they could understand mathematical concepts, solve problems, and succeed in examinations generally achieved higher scores. This finding is consistent with international evidence demonstrating a strong relationship among opportunity to learn, mathematics self-efficacy, and mathematics performance (Wang et al., 2024). Self-efficacy may improve achievement by increasing persistence, strategic effort, willingness to attempt difficult tasks, and tolerance of temporary failure. Students with stronger self-efficacy are also more likely to interpret errors as correctable and to continue working after encountering challenging problems. The present result also aligns with research showing that self-efficacy, together with peer support, predicts mathematics performance among learners in alternative educational settings (Galamiton, 2025). The nonlinear pattern identified in the present model further suggested that the largest predictive gains occurred when students moved from low or moderate self-efficacy to a relatively high level. This indicates that interventions designed to improve competence beliefs may be especially beneficial for students who lack confidence despite possessing adequate prior knowledge.

Study regularity was more influential than the total duration of daily mathematics study. This result indicates that consistent, planned, and repeated engagement with mathematics may be more important than occasional periods of intensive study. Regular practice supports long-term retention, reinforces procedural fluency, allows earlier identification of misunderstandings, and reduces the burden of last-minute preparation. This interpretation is compatible with the literature on self-regulated learning, which emphasizes goal-setting, time management, strategic planning, self-monitoring, and sustained effort as important components of successful mathematics learning (Shaheema et al., 2023). The finding also corresponds with evidence that metacognitive domains predict mathematics performance among senior high school students (Catador, 2024). Students who study regularly are more likely to plan their learning, evaluate their progress, recognize errors, and revise ineffective strategies. Thus, the predictive contribution of study regularity may reflect not only the frequency of studying but also the broader quality of students' self-regulatory processes.

Academic motivation also showed a positive association with mathematics performance, although its independent contribution in the final model was smaller than those of self-efficacy and study regularity. Motivation encourages students to invest effort, persist in demanding tasks, and

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assign value to mathematical learning. However, motivation may influence achievement partly through more proximal behaviors, such as regular study, classroom participation, and purposeful engagement with educational resources. This may explain why its relative importance declined after these related variables were included in the model. The positive association between motivation and achievement is consistent with research showing that active teaching methods, including games and projects, can enhance both students' motivation and their mathematics performance (Arefi, 2024). It also aligns with the broader finding that student engagement is positively associated with mathematics achievement and subjective well-being (Wong et al., 2024). Together, these results suggest that motivation contributes most effectively when it is translated into observable and sustained learning behavior.

Test anxiety had a significant negative relationship with mathematics performance and remained an important predictor in the final model. This finding supports evidence that anxiety can interfere with students' academic performance in senior secondary mathematics (Yarkwah et al., 2024). Test anxiety may reduce performance by occupying working-memory capacity with worry, self-critical thoughts, and fear of failure. Even students who have learned the relevant material may struggle to retrieve procedures or maintain concentration during examinations when anxiety is high. The importance of anxiety is also consistent with research showing that teachers' mathematics anxiety and mathematics teaching anxiety can predict students' mathematics outcomes (Awofala et al., 2024). This suggests that anxiety operates at both individual and classroom levels. A tense instructional climate, negative feedback, or visible teacher discomfort may reinforce students' perceptions that mathematics is threatening. Therefore, the negative contribution of test anxiety in the present model should not be interpreted solely as an individual weakness but as a factor that may be influenced by teaching practices, assessment conditions, and students' earlier learning experiences.

Teacher feedback and support was the most influential educational predictor, followed by perceived instructional quality. Students who reported that their teachers provided clear explanations, corrected errors, responded to questions, and offered constructive feedback generally achieved higher mathematics scores. This finding is directly consistent with research showing that teacher feedback has a positive effect on mathematics performance (Yalçın & Erdoğan, 2023). Effective feedback reduces uncertainty about current performance, helps students distinguish conceptual from procedural errors, and provides guidance regarding the steps necessary for improvement. The interaction observed between teacher feedback and study regularity further suggested that feedback was especially beneficial for students who engaged consistently with course material. These students may be more likely to review corrections, apply recommendations, and incorporate feedback into subsequent problem-solving activities.

The positive contribution of instructional quality is also consistent with causal modeling research highlighting the interconnected roles of curriculum design, classroom management strategies, teacher competence, and mathematics teachers' performance (Dano & Prado, 2024). High-quality instruction is not limited to accurate content presentation; it includes appropriate pacing, the use of multiple representations, meaningful examples, classroom organization, adaptation to students' needs, and opportunities for active participation. The current finding that classroom participation made a smaller but stable contribution reinforces the importance of interactive learning. Students who ask questions, explain solutions, discuss alternative approaches, and participate in problem-solving activities are more likely to process mathematics deeply. Such participation is aligned with research demonstrating that active and project-based teaching methods can strengthen motivation and achievement (Arefi, 2024).

The incremental analysis showed that educational factors increased the proportion of explained variance by 11 percentage points beyond individual variables. This improvement indicates that prediction based only on previous achievement, motivation, self-efficacy, and anxiety would provide an incomplete account of mathematics performance. Students' outcomes are also shaped by what happens in classrooms and by the quality of opportunities available to them. This conclusion is consistent with multilevel evidence showing that mathematics performance reflects the simultaneous influence of factors located at the student, classroom, and educational-system levels (Niu et al., 2025). It also supports findings that opportunity to learn interacts with students' self-efficacy in explaining mathematics performance across diverse educational contexts (Wang et al., 2024). Accordingly, interventions directed exclusively at students may be insufficient when instructional quality, feedback, or opportunities for active learning remain weak.

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Learning technology factors further improved the predictive model, increasing the explained variance from 65% to 72%. Educational use of learning technologies was the most influential variable in this domain, whereas simple access to devices had a comparatively weak relationship with performance. This distinction is theoretically and practically important. Access provides the possibility of technology-supported learning, but it does not ensure that students use digital resources purposefully, regularly, or effectively. The positive association between educational technology use and mathematics performance is consistent with research showing that interactive mathematics software can improve students' achievement by supporting exploration, visualization, and immediate feedback (Uwineza et al., 2023). It also agrees with findings that tablet-based digital games can enhance mathematics learning performance (Tepho & Srisawasdi, 2023) and that adaptive game-based mobile learning can improve mathematics outcomes among students with learning disabilities (Samavati et al., 2024). In addition, the positive effect of Wordwall artificial intelligence on agentic engagement and mathematics performance supports the potential value of AI-assisted learning environments that encourage active student participation (Allahkarami, 2025).

The positive contribution of digital learning competence showed that students benefited more from educational technologies when they possessed the skills required to locate, evaluate, and use digital resources effectively. The interaction between educational technology use and digital competence indicated that frequent use alone was insufficient. Students who lacked the ability to assess the reliability of online information or select appropriate resources received less predictive benefit from technology use. This interpretation is compatible with research on technology-supported process assessment through GeoGebra, which shows that digital tools can produce meaningful learning and assessment information when their use is integrated into appropriate mathematical tasks (Oh, 2024). Similarly, tailored technology-supported assessment has been shown to improve senior secondary mathematics achievement by adapting testing conditions to students' learning needs (Omale, 2024). Therefore, digital competence should be understood as an educational capability rather than merely a technical skill.

Digital distraction had a negative contribution to predicted mathematics performance. Students who frequently used devices for non-academic activities, multitasked during study, or experienced interruptions from digital media generally obtained lower predicted scores. This finding explains why technology access alone was a weak predictor and why high levels of general device use did not necessarily correspond to improved achievement. The beneficial effect of technology depends on whether digital resources support sustained cognitive engagement or fragment students' attention. The model's identification of simultaneous positive and negative technology-related pathways demonstrates the advantage of multidimensional artificial intelligence analysis. A conventional comparison between technology users and non-users might obscure this distinction, whereas the present model separated educational use, competence, perceived usefulness, and distraction.

The model interpretation results also revealed interactions among several predictors. Self-efficacy altered the predicted outcome of students with similar prior achievement, teacher feedback was more beneficial among students with regular study patterns, and educational technology use had a stronger positive effect among digitally competent students. Such interaction patterns help explain why machine-learning models outperformed linear regression. They are also consistent with interpretability-based research showing that artificial intelligence can reveal heterogeneous pathways underlying disparities in mathematics performance (Gomez-Talal et al., 2024). Rather than assuming that every factor has the same effect for every student, interpretable machine learning can identify the conditions under which a factor becomes more or less influential. This feature increases the practical relevance of the model because it can inform differentiated educational support.

The findings also demonstrated the broader usefulness of artificial intelligence for examining performance-related outcomes. Research in other educational and occupational settings has shown that machine-learning and deep-learning approaches can model complex relationships among psychological, behavioral, and contextual variables (Chen, 2024; Li, 2025). However, the present study extends this approach to the prediction of twelfth-grade mathematics performance using an integrated and educationally interpretable framework. Unlike models that emphasize predictive accuracy alone, the current analysis identified modifiable predictors that may support intervention, including self-efficacy, study regularity, anxiety, teacher feedback, instructional quality, purposeful technology use, and digital distraction.

Overall, the results support a multidimensional account of mathematics performance. Prior achievement provided

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the strongest foundation for prediction, but psychological, behavioral, instructional, and technological variables contributed meaningful additional information. The final model's relatively low error and strong test-set explanatory power indicate that artificial intelligence can be used to estimate students' mathematics performance with useful accuracy. Nevertheless, the model should be considered a decision-support instrument rather than a deterministic classification system. Predictions represent probabilities based on observed patterns and should be interpreted alongside teachers' knowledge of students, classroom evidence, and changes in learning conditions.

This study had several limitations. First, the final analytical sample consisted of 84 students, which is relatively small for the development of machine-learning models and may limit the stability of estimates, particularly for complex interactions and subgroup comparisons. Although repeated cross-validation, regularization, restricted model complexity, and an independent test subset were used to reduce overfitting, the model requires external validation in larger samples. Second, the participants were twelfth-grade experimental sciences students from Isfahan, and the findings may not generalize to students in other academic tracks, grade levels, cities, rural settings, or educational systems. Third, several individual, educational, and technology-related predictors were measured through self-report questionnaires and may therefore have been influenced by social desirability, inaccurate recall, or differences in students' interpretation of items. Fourth, the cross-sectional design permitted prediction but did not establish causal relationships. Variables identified as important predictors should not automatically be interpreted as direct causes of mathematics performance. Fifth, the removal of a substantial number of incomplete or invalid questionnaires may have introduced selection bias if students with incomplete data differed systematically from those included in the final analysis. Finally, the test subset was small, and estimates of model performance across gender, school type, and achievement groups should be interpreted cautiously.

Future studies should replicate the model using larger and more diverse samples drawn from several provinces, school types, academic tracks, and socioeconomic contexts. Longitudinal designs should be used to examine whether the predictors identified in this study forecast changes in mathematics performance over time and to distinguish stable student characteristics from short-term learning conditions. Researchers should incorporate objective indicators such as attendance records, digital platform logs, homework completion, item-level assessment data, response times, and patterns of interaction with online resources. External validation should be conducted using a completely independent sample, and the performance of the model should be evaluated across demographic and educational subgroups to identify possible bias. Future research should also compare additional algorithms and use explainable artificial intelligence methods to clarify individual predictions. Experimental and intervention studies are needed to determine whether modifying high-importance variables, such as self-efficacy, study regularity, teacher feedback, test anxiety, educational technology use, and digital distraction, leads to measurable improvements in mathematics achievement.

Schools may use the findings to develop multidimensional screening systems that combine previous achievement with students' self-efficacy, study behavior, anxiety, instructional experiences, and patterns of technology use. Students identified as being at risk should not receive a single uniform intervention. Those with weak prerequisite knowledge may require targeted remedial instruction, whereas students with adequate knowledge but low self-efficacy may benefit from mastery-oriented tasks, constructive feedback, and gradual increases in problem difficulty. Teachers should provide timely and specific feedback, promote regular study routines, use active instructional strategies, and create assessment conditions that reduce unnecessary anxiety. Educational technologies should be selected according to their instructional purpose and integrated into classroom activities rather than introduced merely because they are available. Schools should also teach digital self-regulation and help students distinguish productive learning activities from distracting device use. Any artificial intelligence model used in practice should remain transparent, periodically recalibrated, and subordinate to professional educational judgment.

Authors' Contributions

All authors significantly contributed to this study.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

In this study, to observe ethical considerations, participants were informed about the goals and importance of the research before the start of the interview and participated in the research with informed consent.

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