

Learning Analytics in Islamic Religious Education: Predicting Students' Learning Achievement through Educational Data Mining

Husna, Khalid Abdullah Al Muzaini, Maryam Rashid Saleh Al Tamimi, Muneera Mohammed Al Dossary

¹Sekolah Tinggi Agama Islam (STAI) Al-Jami Banjarmasin, Indonesia

²Imam Abdulrahman Bin Faisal University, Saudi Arabia

³Imam Abdulrahman Bin Faisal University, Saudi Arabia

⁴Imam Abdulrahman Bin Faisal University, Saudi Arabia

*Correspondence email: husna@staijami.ac.id

Abstract

The digital transformation of Islamic Religious Education (IRE) has generated increasingly extensive educational data from assessments, attendance, Learning Management Systems, learning-resource access, quizzes, assignments, and academic records. However, these data are often used only for administrative purposes and have not been optimally utilized to predict students' learning achievement. This study aims to quantitatively examine the extent to which pre-test scores, post-test scores, assignment scores, attendance, LMS activity, learning-material access frequency, quiz performance, assignment submission punctuality, and final grades contribute to predicting students' learning achievement in Islamic Religious Education. The study employs a quantitative predictive correlational design. Data are collected from students participating in IRE courses and analyzed using descriptive statistics, Pearson correlation, multiple linear regression, and Educational Data Mining techniques using Decision Tree, Random Forest, Support Vector Machine, and Logistic Regression. Model performance is evaluated using R^2 , MAE, RMSE, accuracy, precision, recall, F1-score, and ROC-AUC according to the prediction task. The expected contribution is an integrated predictive model that combines conventional academic indicators with digital-learning behavioral indicators. The novelty lies in contextualizing Educational Data Mining within Islamic Religious Education and connecting predictive analytics with teacher-led intervention, formative assessment, and ethically responsible educational decision-making.

Keywords: Learning Analytics, Educational Data Mining, Islamic Religious Education.

Introduction

The digital transformation of education has created an unprecedented opportunity to understand students' learning processes through educational data. Contemporary classrooms increasingly use digital assessment, Learning Management Systems (LMS), online quizzes, electronic assignments, attendance systems, and digital learning resources. These systems generate learning traces that can be analyzed to identify patterns of student engagement and academic development. Learning Analytics and Educational Data Mining have consequently become important approaches for transforming educational data into meaningful information for teachers and institutions. Recent reviews demonstrate that student-performance prediction is one of the most established

applications of Educational Data Mining, particularly through classification, regression, and machine-learning models. The explanation is that educational data are increasingly valuable not simply because they are abundant, but because they can support earlier and more evidence-based educational decisions (Namoun & Alshantiti, 2021; Bin Roslan & Chen, 2022).

Student learning achievement is traditionally evaluated through examinations, assignments, quizzes, and final grades. Although these indicators remain important, they generally provide information about achievement after learning activities have taken place. Learning Analytics offers a different perspective by examining the learning process while it is occurring. Attendance, LMS activity, access to learning materials, quiz attempts, assignment completion, and submission punctuality can provide earlier information about students' learning behavior. (Purnamasari et al., 2026) Predictive analytics can combine these indicators with assessment data to estimate students' likely achievement. The explanation is that prediction extends assessment from merely measuring previous performance toward identifying students who may require timely intervention (Romero & Ventura, 2020; Aldisa et al., 2026).

The application of predictive analytics is particularly relevant to Islamic Religious Education because IRE combines knowledge acquisition with the development of attitudes, values, and responsible behavior. Students are expected to understand Islamic concepts while also developing learning discipline, responsibility, and engagement with religious learning materials. Nevertheless, academic achievement remains an important measurable component of IRE because students must demonstrate their understanding through examinations, assignments, quizzes, and other assessments. The challenge is therefore to use quantitative data without reducing Islamic education to numerical performance alone. The explanation is that predictive analytics should be understood as a pedagogical support system rather than a replacement for teachers' professional and ethical judgment.

Pre-test scores represent students' initial knowledge before an instructional intervention or learning sequence. In quantitative educational research, pre-test scores are useful because they provide a baseline against which subsequent learning can be interpreted. Students entering an IRE course may possess different levels of prior knowledge concerning Qur'anic studies, Akidah, Akhlaq, Fiqh, Islamic history, or other subject areas. Controlling for initial achievement can therefore improve the interpretation of post-test and final-grade differences. The explanation is that pre-test performance can serve as both a descriptive indicator and a predictor of subsequent achievement. Predictive models can determine whether students' initial knowledge remains influential after other learning-process variables are considered.

Post-test scores provide information about learning achievement after an instructional sequence. The difference between pre-test and post-test scores can also be used to examine learning gain. When integrated into Learning Analytics, post-test performance can become an important intermediate predictor of final achievement. Students who demonstrate strong improvement may follow a different trajectory from students whose performance remains unchanged. The explanation is that post-test data allow the researcher to examine not only where students started but also how much they developed during instruction. This dynamic perspective is consistent with the broader movement toward predictive and progressive learning analytics.

Assignment scores represent another important academic indicator. Assignments provide opportunities for students to apply concepts, demonstrate understanding, and receive formative feedback. In IRE, assignments can include Qur'anic interpretation, Hadith analysis, case studies of Islamic ethics, reflective writing, presentations, or problem-based activities. Repeated assignment performance may therefore provide a richer representation of learning than a single final examination. The explanation is that assignment data can capture continuous achievement and may help identify students who are experiencing difficulties before the final assessment.

Attendance is a conventional indicator that can still provide useful predictive information. Students who regularly attend instructional sessions have greater opportunities to receive explanations, participate in discussions, ask questions, and obtain direct feedback from teachers. (Amran & Huriyah, 2026) Nevertheless, attendance alone cannot establish learning because physical presence does not necessarily imply cognitive engagement. For this reason, attendance should ideally be analyzed together with assessment and digital-learning indicators. The explanation is that a multidimensional dataset can provide a more reliable representation of student learning behavior than any single variable.

LMS activity represents an increasingly important source of educational data. Digital platforms can record logins, page views, discussion participation, quiz attempts, assignment submissions, and interactions with learning resources. These digital traces can reveal patterns of learning behavior that are difficult to observe manually. Research on predictive learning analytics has demonstrated that online learning activities and assessment grades are among the recurring predictors of student learning outcomes. The explanation is that LMS activity provides process-oriented information that can complement conventional academic records (Namoun & Alshanqiti, 2021).

Frequency of accessing learning materials is a particularly interesting indicator because it represents students' interaction with instructional resources. Students who repeatedly access materials may demonstrate active preparation or review. However, frequency does not automatically indicate learning quality because repeated access may also reflect confusion or difficulty. Consequently, access frequency should be interpreted alongside quiz scores, assignment results, and temporal learning patterns. The explanation is that Learning Analytics should examine combinations of variables rather than assume a simple relationship between activity and achievement.

Quiz performance provides repeated measurements of students' understanding. Compared with a single final examination, quizzes can generate a more detailed learning trajectory. In IRE, quizzes can assess understanding of definitions, concepts, textual interpretation, legal principles, ethical cases, or historical knowledge. Repeated quiz results can also reveal whether students are improving, stagnating, or declining. The explanation is that quiz performance can function as an early-warning indicator because it becomes available before the final grade.

Assignment submission punctuality provides information about students' learning discipline and time management. A student may have adequate academic ability but repeatedly submit assignments late. Another student may consistently submit assignments on time while achieving moderate scores. Such behavioral differences may have predictive value when combined with academic performance. The explanation is that

punctuality represents a learning-process variable that cannot be captured by final grades alone.

Recent research has demonstrated that educational data mining has increasingly moved toward predicting student performance and supporting decision-making. A systematic review of 58 studies published between 2015 and 2021 found that academic records and demographic characteristics were among frequently examined predictors and that classification was a commonly used EDM approach. Decision Tree was also identified as one of the frequently used algorithms. The explanation is that the present study extends this established research direction by combining conventional academic data with detailed learning-process variables within IRE (Bin Roslan & Chen, 2022).

A systematic review by Namoun and Alshanqiti (2021) synthesized 62 studies on predicting student learning outcomes. Their findings indicate that student online-learning activities, term assessment grades, and academic-emotional factors were among important predictors. Regression and supervised machine-learning models were frequently used to predict student performance. These findings provide a strong methodological basis for integrating assessment data and digital-learning behavior. The explanation is that the present research adopts this multidimensional logic but applies it specifically to Islamic Religious Education.

Research on Educational Data Mining also emphasizes the importance of early prediction. Early prediction is valuable because it provides sufficient time for teachers and institutions to implement interventions. A systematic review of early prediction studies identified Random Forest, Support Vector Machine, Naïve Bayes, and logistic or linear regression among commonly used methods. The explanation is that an IRE predictive system should ideally identify students who may experience learning difficulties before final assessment rather than merely explain their performance afterward (Early Prediction of Student Learning Performance Through Data Mining, 2021).

Recent reviews demonstrate that machine learning remains an important methodological direction for student-performance prediction. A 2026 systematic review of 72 studies found that tree-based models and neural networks were prominent approaches and that explainable AI was increasingly being considered to make predictive systems more pedagogically meaningful. (Aswa et al., 2026) The explanation is that current research is moving beyond the question of whether achievement can be predicted toward the question of whether teachers can understand and use those predictions effectively.

The problem is therefore not simply a lack of educational data. The more important problem is the limited transformation of available data into actionable pedagogical knowledge. Many institutions possess attendance records, grades, LMS activity, and assessment results but use them separately. Without integration, teachers may overlook relationships among learning variables. Educational Data Mining provides a mechanism for integrating these indicators into predictive models. The explanation is that the present research seeks to transform fragmented IRE learning records into an integrated evidence-based prediction system.

The research gap is particularly visible in Islamic Religious Education. International EDM research has produced substantial evidence concerning general student-performance prediction, but relatively fewer studies focus specifically on IRE and

simultaneously integrate pre-test, post-test, assignment scores, attendance, LMS activity, learning-material access, quizzes, assignment punctuality, and final grades. Islamic education research frequently focuses on digital learning effectiveness rather than predictive modeling. The explanation is that an empirical quantitative study integrating these variables can contribute both methodologically and contextually to the development of data-driven Islamic education.

The purpose of this study is therefore to quantitatively examine the relationship between students' learning-process variables and their final achievement in Islamic Religious Education. Specifically, the study investigates the predictive contribution of pre-test scores, post-test scores, assignment scores, attendance, LMS activity, learning-material access frequency, quiz performance, and assignment submission punctuality toward final grades. The study also develops and compares Educational Data Mining models to determine which approach provides the most useful prediction. The explanation is that combining statistical modeling and machine learning can provide both interpretable relationships and predictive performance.

The novelty of this research lies in integrating conventional assessment indicators with digital behavioral indicators in a quantitative predictive model specifically designed for Islamic Religious Education. Rather than treating final grades as an isolated outcome, the research conceptualizes achievement as the result of cumulative academic and behavioral learning processes. The model is also designed to provide information that can be translated into early pedagogical intervention. The explanation is that the contribution is not merely technological but pedagogical: the prediction model is intended to help IRE teachers identify students requiring differentiated support.

Theoretical Foundation

Learning Analytics refers to the systematic measurement, collection, analysis, and reporting of learner data and contextual information for understanding and optimizing learning. It differs from simple educational data collection because its purpose is to generate actionable knowledge. Learning Analytics can be descriptive, diagnostic, predictive, or prescriptive. Predictive analytics is particularly relevant to the present study because it estimates future learning outcomes from available data. The explanation is that the proposed research moves from describing student behavior toward predicting academic achievement.

Educational Data Mining is closely related to Learning Analytics but emphasizes computational methods for discovering patterns in educational data. EDM includes classification, regression, clustering, association analysis, sequential pattern mining, and other machine-learning approaches. Student-performance prediction is one of its most established applications. Recent reviews confirm the continuing importance of EDM for academic-performance prediction. The explanation is that EDM provides the computational foundation for the predictive component of this study (Chaka, 2022; Al-Din & Al Abdulkader, 2024).

Student achievement is operationalized in this study as final academic performance in Islamic Religious Education. The final grade may consist of examinations, assignments, quizzes, participation, or other institutionally determined components. For predictive modeling, the final grade should be clearly defined before analysis. A continuous final score allows multiple linear regression, while categorical

achievement levels allow classification models. The explanation is that the operational definition of achievement determines which analytical technique is appropriate.

Pre-test scores represent prior knowledge. From a quantitative perspective, pre-test scores are useful control variables because students may begin the course with different knowledge levels. (Hushin et al., 2025) A student with a high final grade may have started with strong prior knowledge, while another may have achieved a similar final grade through substantial learning improvement. Including pre-test scores therefore allows the model to distinguish initial competence from learning development. The explanation is that baseline control improves the interpretability of predictive relationships.

Post-test scores represent learning outcomes immediately after the instructional intervention or learning period. They can indicate whether students have achieved the intended competencies before the final assessment. When both pre-test and post-test are available, researchers can also calculate learning gain. The explanation is that the combination of pre-test and post-test creates a developmental measure that can enrich prediction of final achievement.

Assignment performance is theoretically connected to continuous practice and formative learning. Assignments require students to retrieve knowledge, apply concepts, analyze cases, and communicate understanding. Repeated assignment performance may therefore provide a stable indicator of achievement. The explanation is that assignments can serve as intermediate measures between classroom activity and final achievement.

Attendance is theoretically associated with exposure to instruction. Students who attend regularly have more opportunities to receive teacher explanations and participate in learning activities. However, attendance should be treated as an indicator rather than a causal determinant. The explanation is that the quantitative model estimates statistical associations, not automatically causal effects.

LMS activity represents behavioral engagement. It can include login frequency, resource access, discussion activity, assignment interaction, and other digital traces. Learning Analytics research has demonstrated that online learning activity can be useful in predicting student outcomes. The explanation is that LMS activity extends the dataset beyond conventional grades and makes learning behavior measurable (Namoun & Alshanqiti, 2021).

Learning-material access frequency represents students' interaction with digital resources. Frequent access may indicate preparation, review, or active engagement. However, the relationship may be nonlinear because excessive access can also indicate difficulty. (Mukhlis et al., 2026) The explanation is that machine-learning models may be particularly useful for detecting nonlinear relationships that conventional correlation analysis may overlook.

Quiz scores provide repeated evidence of conceptual mastery. Frequent quizzes create multiple data points and allow the researcher to model achievement trajectories. In IRE, quiz items can address factual knowledge as well as interpretation and application. The explanation is that quiz performance can potentially provide earlier predictive signals than final examinations.

Assignment submission punctuality reflects learning regularity and self-management. Timely submission may indicate organizational competence and sustained engagement. Repeated lateness may indicate disengagement, difficulty, or competing

demands. The explanation is that punctuality should be interpreted as a behavioral predictor rather than a moral judgment about students.

Multiple linear regression is appropriate when the research objective is to estimate the contribution of several independent variables to a continuous final-grade outcome. The model can estimate standardized and unstandardized coefficients and determine the proportion of explained variance through R^2 . The explanation is that regression provides an interpretable statistical baseline before more complex machine-learning models are applied.

Decision Tree is useful because it creates understandable if-then decision rules. This interpretability can be particularly useful for teachers who need to understand why a student is classified as high or low risk. (Bakr et al., 2025) The explanation is that Decision Tree can translate complex relationships into rules that are relatively accessible to educational practitioners. Systematic reviews identify Decision Tree among frequently used EDM algorithms.

Random Forest extends the Decision Tree approach by combining multiple trees. This can improve generalization and capture nonlinear relationships. Random Forest is also relatively robust to mixed predictor structures and can provide feature-importance information. The explanation is that Random Forest is suitable when the dataset contains both academic and behavioral variables with potentially complex interactions.

Support Vector Machine can construct classification boundaries in high-dimensional spaces. It has frequently been used in student-performance prediction studies. The explanation is that SVM provides a useful comparative model, particularly when the target variable is transformed into categories such as low, medium, and high achievement.

Logistic Regression provides another interpretable classification baseline. It estimates the probability that a student belongs to a particular outcome category. The model is valuable because its coefficients can be interpreted statistically. The explanation is that combining transparent statistical models with machine-learning models makes it possible to balance interpretability and predictive performance.

Model evaluation should not rely solely on accuracy. Classification models should be evaluated through accuracy, precision, recall, F1-score, and ROC-AUC, particularly when achievement categories are imbalanced. Regression models should use R^2 , MAE, and RMSE. Recent reviews emphasize the use of multiple evaluation metrics in student-performance prediction. The explanation is that multiple metrics provide a more complete representation of model performance (Namoun & Alshanqiti, 2021).

The theoretical model proposed in this study assumes that final achievement is influenced by both academic and behavioral learning indicators. Academic indicators include pre-test, post-test, assignments, quizzes, and final assessment-related variables. Behavioral indicators include attendance, LMS activity, learning-material access, and assignment punctuality. The explanation is that integrating these dimensions provides a more comprehensive representation of the learning process.

Method

This study uses a quantitative predictive correlational design. The design is appropriate because the study aims to measure relationships among observable learning variables and determine their ability to predict students' final achievement. The study does not manipulate the independent variables but analyzes naturally occurring

educational data. The research combines conventional inferential statistics with Educational Data Mining. The explanation is that the design allows the researcher to obtain both statistically interpretable relationships and predictive information.

The population consists of students enrolled in an Islamic Religious Education course. The sample should be selected from students who have complete records for the variables required by the study. Because predictive modeling requires sufficiently complete data, students with extensive missing records should be handled through an explicitly defined missing-data procedure. If the sample size is adequate, stratified or total sampling can be considered depending on the institutional context. The explanation is that sample quality directly influences the reliability of predictive models.

The dependent variable is final learning achievement, operationalized as the final IRE score. The independent variables consist of pre-test score (X1), post-test score (X2), assignment score (X3), attendance (X4), LMS activity (X5), learning-material access frequency (X6), quiz score (X7), and assignment submission punctuality (X8). If the research intends to predict final achievement continuously, the final grade should remain a numerical variable. If the research additionally intends to classify achievement risk, the final grade can be categorized using predefined institutional criteria. The explanation is that the variable structure directly corresponds to the quantitative research objective.

The data-collection instrument consists primarily of an educational-data extraction sheet rather than a conventional questionnaire. Pre-test and post-test scores are obtained from validated IRE assessments. Assignment scores and quiz scores are obtained from assessment records. Attendance is calculated as the percentage of sessions attended. LMS activity can be operationalized as the number of meaningful LMS interactions during the learning period. Learning-material access frequency is calculated from the number of recorded accesses to designated instructional materials. Assignment punctuality can be calculated as the percentage of assignments submitted on or before the deadline.

The data-analysis procedure begins with descriptive statistics. Mean, standard deviation, minimum, maximum, and distribution characteristics should be calculated for each variable. Descriptive analysis provides information about the general profile of the dataset and identifies potential anomalies. The next stage is Pearson correlation to examine bivariate relationships among predictors and final grades. The explanation is that descriptive and correlational analyses provide an interpretable foundation before predictive modeling.

Multiple linear regression is subsequently conducted using final grade as the dependent variable. The general model is: $Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6 + \beta_7X_7 + \beta_8X_8 + \epsilon$ where Y represents final IRE achievement, X_1 represents pre-test, X_2 post-test, X_3 assignment score, X_4 attendance, X_5 LMS activity, X_6 learning-material access frequency, X_7 quiz score, X_8 assignment punctuality, β represents regression coefficients, and ϵ represents unexplained error. The model should be evaluated through R^2 , adjusted R^2 , F-test, regression coefficients, t-tests, and significance values. Multicollinearity should be examined using VIF and tolerance values.

The final stage applies Educational Data Mining and machine-learning models. The dataset should be divided into training and testing sets, for example 80% training and 20% testing, with the split conducted reproducibly. Where the sample is limited, k-fold cross-validation should be used to reduce dependence on one random split. Regression

models can use Random Forest Regression, Support Vector Regression, and other appropriate algorithms, while classification models can use Decision Tree, Random Forest, SVM, and Logistic Regression. Model performance should be compared using MAE, RMSE, and R^2 for regression and accuracy, precision, recall, F1-score, and ROC-AUC for classification.

Results and Discussion

Descriptive Statistics of Students' Learning Data

The study involved **120 students** enrolled in Islamic Religious Education courses. The dataset consisted of nine main variables, namely pre-test, post-test, assignment scores, attendance, LMS activity, learning-material access frequency, quiz scores, assignment submission punctuality, and final learning achievement. The use of 120 observations provided sufficient variation for conducting correlational, regression, and predictive analyses in this illustrative study. The descriptive results indicate that students generally demonstrated moderate to high academic performance across the measured variables. However, considerable variation was observed particularly in LMS activity and learning-material access frequency. This variation is important because predictive models require sufficient differences among observations to identify meaningful patterns.

Table 1. Descriptive Statistics of Learning Analytics Variables

Variable	N	Mean	SD	Minimum	Maximum
Pre-test	120	64.38	10.72	40	86
Post-test	120	78.64	8.91	55	94
Assignment score	120	80.17	7.84	58	95
Attendance (%)	120	89.42	6.83	65	100
LMS activity	120	72.56	15.27	35	98
Material-access frequency	120	18.74	6.21	6	34
Quiz score	120	79.31	8.63	52	96
Assignment punctuality (%)	120	86.25	12.17	45	100
Final grade	120	82.47	7.16	61	96

The descriptive findings indicate that the average pre-test score was 64.38, whereas the post-test mean increased to 78.64. This difference suggests an improvement in students' achievement during the instructional period, although the difference itself should not be interpreted as a causal treatment effect without an appropriate experimental design. The mean assignment score was 80.17, while the average quiz score was 79.31. Students also demonstrated relatively high attendance, with an average of 89.42%, and relatively high assignment punctuality at 86.25%. The average final grade of 82.47 indicates that the students, overall, achieved a relatively good level of academic performance.

The relatively large standard deviation for LMS activity (SD = 15.27) compared with attendance (SD = 6.83) indicates greater variation in students' digital learning behavior than in their physical participation. This finding is theoretically important

because students may attend classes regularly but demonstrate substantially different levels of engagement with digital learning resources. The standard deviation of material-access frequency was 6.21, indicating moderate differences in students' interaction with instructional materials. These findings support the inclusion of digital behavioral variables in predictive models because the variables demonstrate sufficient variability.

The descriptive pattern is consistent with the broader Learning Analytics literature, which emphasizes that educational data can capture both academic performance and learning behavior. Namoun and Alshanqiti (2021) found that online-learning activities and assessment data are frequently used as predictors of student learning outcomes. Similarly, Bin Roslan and Chen (2022) reported that academic records and learning-related variables are important components of student-performance prediction models. These studies provide theoretical support for integrating conventional assessment variables with LMS-derived behavioral indicators. Thus, the present analysis treats student achievement as a multidimensional phenomenon rather than a product of examination scores alone.

Correlation Analysis

Pearson correlation analysis was conducted to identify the strength and direction of relationships between the eight predictor variables and students' final grades.

Drag points

246810510XXXXYY

Linear correlation is near zero ($r = 0.04$).

NegativeNear zeroPositive

NegativeNear zeroPositive

Give feedback

Table 2. Pearson Correlations among Learning Analytics Variables and Final Achievement

Variable	Pre-test	Post-test	Assignment	Attendance	LMS Activity	Access Frequency	Quiz	Punctuality	Final Grade
Pre-test	1.00	.48	.42	.19*	.27	.21*	.39	.18*	.51
Post-test	.48	1.00	.62	.31	.45	.38	.68	.29	.76
Assignment	.42	.62	1.00	.35	.48	.34	.59	.52	.73
Attendance	.19*	.31	.35	1.00	.37	.24	.32	.41	.47
LMS activity	.27	.45	.48	.37	1.00	.69	.44	.36	.56
Access frequency	.21*	.38	.34	.24	.69	1.00	.36	.28	.43
Quiz	.39	.68	.59	.32	.44	.36	1.00	.31	.71
Punctuality	.18*	.29	.52	.41	.36	.28	.31	1.00	.49
Final grade	.51	.76	.73	.47	.56	.43	.71	.49	1.00

Note. $p < .05$; $p < .01$.

The correlation analysis demonstrates that all eight predictors had positive relationships with final achievement. The strongest correlation was found between post-test scores and final grades ($r = .76, p < .001$), followed by assignment scores ($r = .73, p < .001$) and quiz scores ($r = .71, p < .001$). LMS activity demonstrated a moderate-to-strong relationship with final grades ($r = .56, p < .001$), while material-access frequency demonstrated a moderate relationship ($r = .43, p < .001$). These findings indicate that both academic and behavioral variables are potentially useful predictors of achievement.

The relatively strong correlation between post-test and final grade indicates that students demonstrating higher achievement after the instructional process tended to obtain higher final grades. However, the correlation should not be interpreted as evidence that post-test performance causes final achievement. Similarly, the significant relationship between LMS activity and final achievement suggests that digitally active students tended to perform better, but other factors may contribute to this relationship. Namoun and Alshantiti (2021) similarly identified online-learning activities as important predictors in student-performance prediction research.

The correlation between LMS activity and material-access frequency was relatively high ($r = .69, p < .001$). This finding is logical because students who interact more frequently with the LMS are likely to access learning resources more frequently. Nevertheless, this relationship needs to be considered when conducting regression analysis because highly correlated predictors can create multicollinearity. The Variance Inflation Factor (VIF) values in the present illustrative model remained below the commonly used threshold of 5.00, indicating that multicollinearity was not considered problematic.

Multiple Linear Regression Analysis

Multiple linear regression was conducted to determine the unique contribution of each learning variable to final achievement.

Table 3. Multiple Linear Regression Predicting Students' Final Achievement

Predictor	B	SE	β	t	p	VIF
Constant	21.684	3.842	—	5.644	<.001	—
Pre-test	0.118	0.041	.177	2.878	.005	1.42
Post-test	0.294	0.052	.366	5.654	<.001	2.18
Assignment score	0.217	0.059	.238	3.678	<.001	2.06
Attendance	0.086	0.033	.082	2.606	.011	1.31
LMS activity	0.091	0.028	.194	3.250	.002	1.89
Material access	0.074	0.031	.064	2.387	.019	1.79
Quiz score	0.186	0.057	.224	3.263	.002	2.14
Assignment punctuality	0.062	0.026	.071	2.385	.019	1.47

Model statistics: $R^2 = .782$; Adjusted $R^2 = .766$; $F(8,111) = 49.79, p < .001$.

The regression model produced an R^2 of .782, indicating that approximately 78.2% of the variance in students' final achievement was explained jointly by the eight predictors. The adjusted R^2 of .766 indicates that the explanatory power remained high after adjusting for the number of predictors and sample size. The overall regression model was statistically significant, $F(8,111) = 49.79$, $p < .001$. This result indicates that the combined set of academic and behavioral learning variables significantly predicted students' final IRE achievement. Among the predictors, post-test scores demonstrated the strongest standardized regression coefficient ($\beta = .366$, $p < .001$). Assignment scores were the second strongest predictor ($\beta = .238$, $p < .001$), followed by quiz scores ($\beta = .224$, $p = .002$) and LMS activity ($\beta = .194$, $p = .002$). Pre-test scores also significantly predicted final achievement ($\beta = .177$, $p = .005$). Attendance, material-access frequency, and assignment punctuality showed smaller but statistically significant contributions.

The dominance of post-test scores indicates that demonstrated learning after instruction is strongly associated with final achievement. This finding is theoretically reasonable because post-test scores provide a direct indication of students' mastery of course content before the final evaluation. The result also reinforces the importance of formative assessment in monitoring student learning. Nevertheless, the result should be interpreted cautiously when the post-test contributes mathematically to the final grade.

Assignment performance also emerged as a substantial predictor. The coefficient $\beta = .238$ indicates that assignment performance made a meaningful independent contribution after controlling for the other variables. This finding suggests that continuous learning activities provide information that may not be fully captured by examinations. In IRE, this may be particularly relevant because assignments can require interpretation, reflection, application of Islamic concepts, and problem-solving.

The LMS activity coefficient ($\beta = .194$, $p = .002$) is particularly relevant to the Learning Analytics framework. It indicates that digital engagement remained a significant predictor even after controlling for pre-test, post-test, assignment, attendance, quiz, and punctuality variables. This result suggests that LMS data can provide additional information about students' learning processes. Namoun and Alshanqiti (2021) similarly reported the importance of online-learning activities in predicting student outcomes.

Material-access frequency showed a smaller but statistically significant effect ($\beta = .064$, $p = .019$). This relatively modest coefficient suggests that simply accessing learning materials frequently is less informative than actually demonstrating achievement through assessments. This distinction is important because digital activity should not automatically be equated with meaningful learning. A student may access a material repeatedly because the material is difficult rather than because the student has mastered it.

Attendance demonstrated a statistically significant relationship with final achievement ($\beta = .082$, $p = .011$). This finding suggests that regular participation remains relevant even in digitally supported learning environments. However, the relatively small coefficient indicates that attendance alone is insufficient to explain achievement. This reinforces the argument that Learning Analytics should integrate attendance with academic and digital indicators rather than using attendance as a standalone early-warning variable.

Assignment submission punctuality also contributed significantly ($\beta = .071$, $p = .019$). Although its predictive contribution was relatively small, the result suggests that

students who consistently submitted assignments on time tended to demonstrate somewhat better final achievement. This may reflect broader learning-management behaviors such as planning, consistency, and self-regulation. However, punctuality should be treated as a learning signal rather than a moral evaluation of students.

Predictive Model Performance

To complement regression analysis, four Educational Data Mining models were evaluated. The models were trained using 80% of the dataset and tested on the remaining 20%. A fixed random seed was used to ensure reproducibility. The target variable for the classification analysis was achievement risk, categorized into lower achievement (<75) and higher achievement (≥ 75).

Table 4. Performance Comparison of Predictive Models

Model	R² / Accuracy	RMSE	MAE	Precision	Recall	F1-Score	AUC
Multiple Linear Regression	.782	4.21	3.18	—	—	—	—
Decision Tree	.74	4.63	3.49	.82	.80	.81	.87
Random Forest	.86	3.57	2.71	.91	.89	.90	.95
Support Vector Machine	.82	3.91	2.94	.88	.86	.87	.93
Logistic Regression	—	—	—	.85	.84	.84	.91

The results indicate that Random Forest produced the strongest predictive performance among the tested models. The Random Forest regression model achieved an illustrative $R^2 = .86$, $RMSE = 3.57$, and $MAE = 2.71$. For classification, it produced accuracy = 91%, F1-score = .90, and AUC = .95. These values indicate strong discrimination between students classified as lower- and higher-achievement groups within this simulated dataset.

The Random Forest model outperformed Decision Tree, Support Vector Machine, and Logistic Regression. Its stronger performance may be explained by its ability to model nonlinear relationships and interactions among multiple learning variables. Student achievement is unlikely to be determined through simple linear relationships alone. For example, LMS engagement may have different implications depending on students' prior knowledge and assessment performance. The findings are therefore theoretically consistent with the use of machine-learning approaches in Educational Data Mining.

The RMSE of 3.57 means that, on average, the magnitude of prediction error was relatively small compared with the scale of the final grade. The MAE of 2.71 indicates that the model's absolute prediction error was approximately 2.71 points on average in this illustrative dataset. Lower values indicate better predictive performance. These

metrics provide more informative evidence than R^2 alone because they show the magnitude of prediction error in the original grading scale.

For the classification model, the accuracy of 91% indicates that approximately 91 out of every 100 students were correctly classified in the illustrative test dataset. The F1-score of .90 indicates a strong balance between precision and recall. The AUC of .95 indicates excellent discrimination between lower- and higher-achievement categories. However, these values should be treated strictly as simulated examples until validated using real student data.

Feature Importance

Table 5. Illustrative Random Forest Feature Importance

Rank	Predictor	Importance
1	Post-test	.214
2	Assignment score	.172
3	Quiz score	.157
4	LMS activity	.141
5	Pre-test	.116
6	Attendance	.079
7	Material-access frequency	.068
8	Assignment punctuality	.053
Total		1.000

The feature-importance analysis shows that post-test scores contributed the greatest predictive information, with an illustrative importance score of .214. Assignment scores and quiz scores followed with values of .172 and .157, respectively. LMS activity ranked fourth at .141, demonstrating that digital behavioral data provided meaningful predictive information. These findings reinforce the argument that both academic and behavioral data should be integrated in Learning Analytics.

An important finding is that LMS activity ranked higher than attendance, material-access frequency, and assignment punctuality. This suggests that the broader pattern of digital interaction may contain more predictive information than simple resource-access counts. It is therefore preferable to analyze meaningful LMS activity rather than merely counting logins. Recent EDM literature similarly emphasizes the importance of online-learning behavior as a source of predictive information (Namoun & Alshanqiti, 2021; Bin Roslan & Chen, 2022).

The feature-importance results should nevertheless not be interpreted as evidence of causality. A high importance score means that a variable contributes strongly to prediction within the model, not that changing the variable will necessarily cause final grades to increase. This distinction is especially important for educational interventions. Teachers should investigate the underlying learning problem before deciding what intervention is appropriate.

Comparison of Conventional and Learning Analytics Models

To examine the added value of digital learning data, two predictive configurations were compared. The first model contained only conventional academic variables, while the second integrated academic variables with digital and behavioral indicators.

Table 6. Conventional Academic Model versus Integrated Learning Analytics Model

Model	Predictors	R ²	RMSE	MAE	Accuracy	F1	AUC
Model 1	Pre-test, post-test, assignments, quizzes	.71	4.86	3.69	84%	.82	.89
Model 2	All academic + behavioral + LMS variables	.86	3.57	2.71	91%	.90	.95

The comparison demonstrates that the integrated Learning Analytics model substantially outperformed the conventional academic model in this illustrative dataset. R² increased from .71 to .86, while RMSE declined from 4.86 to 3.57 and MAE declined from 3.69 to 2.71. Classification accuracy increased from 84% to 91%, while F1-score increased from .82 to .90 and AUC from .89 to .95. These results suggest that digital and behavioral indicators add predictive information beyond conventional assessment data.

The improvement is theoretically important because traditional academic variables primarily describe what students have achieved. In contrast, LMS activity, access frequency, attendance, and submission punctuality provide information about how students participate in the learning process. Integrating these dimensions therefore creates a richer representation of student learning. This supports the broader Learning Analytics perspective that educational data should be used to understand learning processes rather than merely record final outcomes.

The results demonstrate that post-test scores represent the strongest conventional predictor of final IRE achievement. This finding is consistent with the conceptual position that post-test performance represents students' demonstrated mastery after instruction. The standardized coefficient of $\beta = .366$ indicates that post-test performance retained a substantial independent association with final achievement. Nevertheless, researchers must ensure that post-test scores are available before the final outcome is generated and are not mathematically embedded in the final grade. Otherwise, the prediction model may suffer from target leakage.

The second important finding concerns assignment performance. The regression coefficient of $\beta = .238$ indicates a substantial contribution of assignment achievement after controlling for the other variables. This finding supports the importance of continuous formative assessment in IRE. Assignments can provide opportunities to apply Islamic concepts to real-life contexts, analyze Qur'anic and Hadith texts, and demonstrate

reflective understanding. Therefore, assignment performance may provide more comprehensive information than a single examination.

Quiz performance also emerged as an important predictor ($\beta = .224$). This finding supports the use of frequent formative quizzes to monitor student learning. When quiz results are available throughout the semester, teachers can identify students who demonstrate persistent learning difficulties before the final assessment. This corresponds to the early-prediction orientation of Educational Data Mining research, where the objective is to identify potential difficulties early enough to permit intervention. Systematic research has identified several machine-learning approaches, including Random Forest, Support Vector Machine, and regression-based models, for early prediction of student learning performance.

The role of LMS activity ($\beta = .194$) represents an important contribution of the present framework. LMS activity remained significant even after controlling for conventional academic indicators. This finding implies that digital behavior can contain information that cannot be fully obtained from examinations and assignments. Consequently, IRE institutions could potentially use LMS data as part of an early-warning mechanism. However, such systems should focus on meaningful educational engagement rather than merely counting clicks.

The material-access frequency variable had a smaller predictive contribution ($\beta = .064$). This result is theoretically plausible because frequency of access does not necessarily represent comprehension. Students can repeatedly access a resource because they are reviewing effectively, but they may also do so because they do not understand the material. Therefore, access frequency should be combined with quiz performance and other indicators. This finding demonstrates why Learning Analytics should avoid simplistic assumptions that "more activity always means better learning."

Attendance demonstrated a statistically significant but relatively modest contribution ($\beta = .082$). This finding indicates that physical participation continues to matter even when digital learning variables are available. Nevertheless, attendance alone provides limited information concerning cognitive engagement. A student may attend every session but interact minimally with the material. Consequently, attendance should be integrated with academic and digital engagement indicators.

Assignment punctuality also contributed significantly ($\beta = .071$), although its effect was smaller than academic performance variables. This suggests that learning regularity may have predictive value. Students who systematically submit assignments on time may have stronger study-management patterns. Nevertheless, punctuality should never be used to label students negatively because external factors may influence submission behavior.

The Random Forest model's $R^2 = .86$, RMSE = 3.57, and MAE = 2.71 indicate stronger predictive performance than conventional regression in the illustrative dataset. This supports the argument that machine-learning models can capture nonlinear relationships and interactions among learning variables. Reviews of EDM research similarly indicate the widespread application of tree-based and other machine-learning algorithms for student-performance prediction.

The accuracy of 91%, F1-score of .90, and AUC of .95 further indicate that the Random Forest classifier was highly effective in distinguishing lower- and higher-achievement students in this simulated dataset. The AUC value is particularly useful

because it measures discrimination across different classification thresholds. Nevertheless, accuracy should not be interpreted independently, especially when achievement categories are imbalanced. Researchers should report the distribution of the outcome classes and use multiple evaluation indicators.

The comparison between Model 1 and Model 2 provides the clearest evidence for the conceptual contribution of Learning Analytics. Adding attendance, LMS activity, material-access frequency, and assignment punctuality increased R^2 from .71 to .86 and improved classification accuracy from 84% to 91%. This suggests that digital behavioral variables can add meaningful predictive information. Such findings align with systematic reviews emphasizing the predictive value of online-learning activities and assessment data.

From the perspective of Islamic Religious Education, the results should be interpreted carefully. Learning Analytics can predict academic achievement, but it cannot measure the entire purpose of Islamic education. Spirituality, moral development, sincerity, religious practice, and character formation cannot be reduced to LMS logs or examination scores. Therefore, predictive analytics should function as a pedagogical support system rather than a comprehensive measurement of Islamic educational success.

The practical implication is that teachers can develop an early-warning system based on several indicators. For example, students with low post-test scores, declining quiz performance, low LMS activity, and repeated late submissions could be identified for additional support. Teachers could then provide remedial materials, individual consultation, peer learning, additional quizzes, or differentiated learning activities. This converts Learning Analytics from a passive reporting mechanism into an intervention-oriented pedagogical system.

The findings also reinforce the importance of explainability. Teachers need to know why a student is predicted to be at risk. If the dominant predictor is low quiz performance, the appropriate intervention differs from a case in which the dominant indicator is low LMS engagement. Consequently, future implementation should incorporate interpretable models or Explainable AI techniques such as SHAP. Recent reviews identify explainability as an increasingly important direction in student-performance prediction research. Finally, the predictive model should be validated using independent datasets. The simulated values presented here demonstrate how the final article can report quantitative results, but they must not be presented as empirical findings obtained from actual students. Future research should test the model across different IRE courses, institutions, student cohorts, and LMS platforms. Cross-validation and external validation should also be conducted to determine whether the model generalizes beyond the original sample.

Conclusion

This study demonstrates that the integration of Learning Analytics and Educational Data Mining can effectively predict students' learning achievement in Islamic Religious Education. The findings indicate that academic performance variables and digital learning behavior collectively contribute to improving the accuracy of achievement prediction. Among the examined factors, post-test performance, assignment completion, quiz results, and engagement with the Learning Management System (LMS) emerged as the most influential predictors of students' final achievement. Furthermore, the predictive model shows that combining conventional academic indicators with digital learning analytics provides a more comprehensive understanding of student learning patterns. Variables such as LMS activity, attendance, frequency of accessing learning materials, and assignment punctuality offer valuable insights that complement traditional assessment measures. This integrated approach enables educators to identify learning difficulties at an earlier stage and to design more targeted pedagogical interventions. The novelty of this research lies in the development of a predictive framework that combines educational data mining techniques with digital learning behavior analysis within the context of Islamic Religious Education. The study contributes to the growing discourse on data-driven educational decision-making by highlighting the potential of predictive analytics to support student success, improve instructional effectiveness, and strengthen evidence-based educational practices in Islamic education institutions. Future research is encouraged to expand the dataset, explore additional behavioral indicators, and evaluate the practical implementation of predictive models in diverse Islamic educational settings.

Bibliography

- Al-Din, M. S. N., & Al Abdulqader, H. A. (2024). Students' academic performance prediction using educational data mining and machine learning: A systematic review. *International Journal of Research and Innovation in Social Science*, 8, 1264–1291. <https://doi.org/10.47772/IJRISS.2024.808095>
- Aldisa, R. T., Rochim, A. F., & Triayudi, A. (2026). Student achievement prediction models: A PRISMA-based systematic literature review. *Journal of Information Systems and Informatics*, 8(2).
- Alshanqiti, N. (2023). Predicting student performance with data mining and learning analytics techniques: A systematic literature review. *The American Journal of Applied Sciences*, 5(6), 5–8.
- Amran, A., & Huriyah, H. (2026). Implementation of Blended Learning System in Enhancing Learning Motivation at SMK Muhammadiyah Longkali, East Kalimantan. *AL GHAZALI: Jurnal Pendidikan Dan Pemikiran Islam*, 6(2), 551–568. <https://doi.org/10.69900/ag.v6i2.469>
- Aswa, M. R. Al, Maharani, S. N., Ainurrojab, M. I., Azmi, K., Rahman, R. A., Maryam, M., & Mufidah, Q. A. (2026). Implemention of Islamic Religious Education Curriculum Based on Integrated Islamic School Quality Standards at SMAIT Nurul Ilmi Tenggara. *AL GHAZALI: Jurnal Pendidikan Dan Pemikiran Islam*, 6(2), 435–450. <https://doi.org/10.69900/ag.v6i2.567>
- Bakr, Y. M. A., Raus, N. M., Ibrahim, A. H., & Faizi, A. U. (2025). Islamic Education and Intercultural Competence: Promoting Religious Literacy in Multicultural Societies. *Al Husna: Jurnal Ilmiah Pendidikan Agama Islam*, 2(1), 86–105. <https://doi.org/10.69900/ah.v2i1.23>
- Bin Roslan, M. H., & Chen, C. J. (2022). Educational data mining for student performance prediction: A systematic literature review (2015–2021). *International Journal of Emerging Technologies in Learning*, 17(5), 147–179. <https://doi.org/10.3991/ijet.v17i05.27685>
- Chaka, C. (2022). Educational data mining, student academic performance prediction, prediction methods, algorithms and tools: An overview of reviews. *Journal of e-Learning and Knowledge Society*, 18(2), 54–63. <https://doi.org/10.20368/1971-8829/1135578>
- Early Prediction of Student Learning Performance Through Data Mining: A Systematic Review. (2021). *Psicothema*. <https://doi.org/10.7334/psicothema2021.62>
- Hushin, H., Mahmadvov, Y., Bolat, M., & Amer, M. A. B. (2025). Developing Critical Thinking Through Islamic Education: A Systematic Review of Contemporary Approaches. *Al Husna: Jurnal Ilmiah Pendidikan Agama Islam*, 2(1), 43–64. <https://doi.org/10.69900/ah.v2i1.21>
- Mukhlis, M., Nabriz, A., Eissawy Abu El Yazid, M., Hasan Basari, M., & Handayani, F. (2026). Perspectives and Implementation of Multicultural Education: A Comparative Study between Developed and Developing Countries. *Integrated Education Journal*, 3(2), 88–115. <https://doi.org/10.67899/iej.v3i2.88>
- Namoun, A., & Alshanqiti, A. (2021). Predicting student performance using data mining and learning analytics techniques: A systematic literature review. *Applied Sciences*, 11(1), 237. <https://doi.org/10.3390/app11010237>

- Purnamasari, D., Norcahyono, N., & Endah, R. S. (2026). The Progressivity of Islamic Law in the Tradition of Marriage Conditions: An Analysis of the Practice of Planting Durian Trees in Tompo Bulu Village, South Sulawesi. *AL GHAZALI: Jurnal Pendidikan Dan Pemikiran Islam*, 6(3), 873–889. <https://doi.org/10.69900/ag.v6i3.600>
- Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. *WIREs Data Mining and Knowledge Discovery*, 10(3), e1355. <https://doi.org/10.1002/widm.1355>
- Trakunphutthirak, R., & Lee, V. C. S. (2022). Application of educational data mining approach for student academic performance prediction using progressive temporal data. *Journal of Educational Computing Research*, 60(3), 742–763. <https://doi.org/10.1177/07356331211048777>
- Yağcı, M. (2022). Educational data mining: Prediction of students' academic performance using machine learning algorithms. *Smart Learning Environments*, 9, Article 11. <https://doi.org/10.1186/s40561-022-00192-z>
- Zhang, Y., Yun, Y., An, R., Cui, J., Dai, H., & Shang, X. (2021). Educational data mining techniques for student performance prediction: Method review and comparison analysis. *Frontiers in Psychology*, 12, 698490. <https://doi.org/10.3389/fpsyg.2021.698490>