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Prediction Model of Batam University Management Information System Based on Regression and Machine Learning

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ABSTRACT

The implementation of Management Information Systems (MIS) in higher education is strongly influenced by the use of information technology (IT) and the digital competence of its users. This study aims to analyze the influence of IT use and digital competence on MIS at Batam University, as well as to develop the best prediction model by comparing conventional statistical methods and machine learning algorithms. Research data were collected through a Likert-scale-based questionnaire from respondents selected using a purposive sampling technique. Data analysis was performed using a combination of Multiple Linear Regression, Random Forest Regressor, and Gradient Boosting Regressor. The results of statistical tests indicate that the use of IT and digital competence simultaneously have a positive and significant effect on MIS with a coefficient of determination (R^2) of 87.40%. On the other hand, the results of the machine learning model evaluation show that Random Forest Regressor provides the best performance with the lowest MAE and RMSE values, and the highest prediction accuracy (R^2 Score) reaching 0.905072. This study concludes that the integration of statistical and machine learning approaches can produce an accurate and adaptive MIS prediction model to support data-driven decision making at Batam University.

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1. Introduction

The development of information technology in the digital era has driven significant transformations in organizational management, including higher education. Management Information Systems (MIS) are a strategic component supporting operational effectiveness, decision-making, academic data management, administration, and improving the quality of educational services. Higher education institutions are required to optimally integrate information technology to improve the efficiency, accuracy, and speed of institutional services.[1]In the context of higher education, MIS implementation depends not only on technological infrastructure but also on the ability of human resources to utilize that technology. The use of information technology (IT) and digital competency are critical factors in determining the effectiveness of MIS implementation. The greater the user's ability to understand and utilize digital technology, the more optimal the MIS implementation will be in supporting organizational activities.

Batam University, as one of the universities continuously undergoing digital transformation, faces challenges in optimizing its technology-based management information system. The use of various academic applications, digital administration systems, and the integration of technology-based services requires users to adapt to developments in information technology. However, differences in IT usage and digital competency among users often impact the effectiveness of management information system implementation in higher education environments. On the other hand, the development of machine learning opens up new opportunities in developing data-driven predictive models that are more accurate and adaptive than conventional statistical approaches. Machine learning enables systems to automatically learn data patterns to produce more effective predictions to support organizational decision-making. This technology is beginning to be widely applied in various fields, including information systems management and organizational performance prediction.[2].

The linear regression approach has been widely used in research to analyze relationships between variables due to its clear statistical interpretation. However, developments in machine learning methods such as Random Forest and Gradient Boosting have demonstrated improved predictive capabilities in handling complex data. Therefore, combining regression and machine learning approaches is crucial for producing predictive models that are not only interpretive but also highly accurate.[3].

Several previous studies have examined the application of regression and machine learning in various fields.Farhanuddin et al., (2024)studied the comparison of Multiple Linear Regression and Random Forest Regression in predicting information system project budgets. The results showed that Random Forest had a higher level of accuracy than conventional linear regression. Research by[4]applied linear regression and Random Forest algorithms to predict perfume sales using the CRISP-DM approach. The study demonstrated that machine learning can improve prediction accuracy compared to conventional statistical methods. Furthermore, the study[5]implemented Random Forest Regression to predict supermarket sales and found that machine learning algorithms were able to process transaction data more effectively in producing operational predictions.

Meanwhile, research[1]This paper discusses the integration of business information systems with machine learning technology to improve the efficiency of data-driven organizational decision-making. Although various previous studies have discussed the application of regression and machine learning, most of the research still focuses on sales prediction, project management, supply chain management, and business forecasting. Research specifically discussing predictive models for Management Information Systems in higher education based on a combination of regression and machine learning is still relatively limited, particularly in the context of higher education in Indonesia.

Based on these conditions, this study has a novelty in the development of a predictive model for the Management Information System of Batam University by combining a linear regression statistical approach and machine learning algorithms such as Random Forest Regressor and Gradient Boosting Regressor. This study not only analyzes the influence of IT usage and digital competence on the Management Information System, but also conducts a comparative evaluation of the accuracy level of the predictive model to obtain the best model in supporting data-based decision making in the higher education environment. Thus, this study is expected to be able to provide theoretical contributions in the development of machine learning-based management information system studies and provide practical contributions for Batam University in improving the effectiveness of information system management through a more modern, accurate, and adaptive predictive approach to the development of digital technology.

2. Research Method

This study uses a quantitative approach with predictive methods based on statistical regression and machine learning to analyze and predict the Management Information System (MIS) at Batam University. The quantitative approach was chosen because it is able to explain the relationship between variables objectively through numerical analysis and statistical testing. The research model uses a combination of Multiple Linear Regression, Random Forest Regressor, and Gradient Boosting Regressor to compare the level of model prediction accuracy. The linear regression approach is used to statistically determine the effect of independent variables on the dependent variable, while machine learning is used to improve the predictive ability of the data-based model. The use of a combination of regression and machine learning is considered relevant in modern information systems research because it is able to produce statistical interpretations and more accurate predictions based on digital data.[6]. The independent variables in this study consist of two factors, namely IT Usage (X1) and Digital Competence (X2). Meanwhile, the dependent variable is the Management Information System (Y). Thus, this study aims to analyze the influence, both partially and simultaneously, of IT Usage and Digital Competence on the implementation or performance of the Management Information System.

2.1.Research Procedure

The research stages were carried out systematically, starting from data collection to machine learning model evaluation. This study adapted the CRISP-DM (Cross Industry Standard Process for Data Mining) stages, which include business understanding, data understanding, data preparation, modeling, evaluation, and simple deployment in the form of interpreting research results.[7]. The research stages are shown as follows:

1. Identification of research problems in the Management Information System of Batam University.
2. Determination of research variables based on previous theory and research.
3. Preparation of research instruments based on the Likert scale.
4. Respondent data collection.
5. Data preprocessing includes cleaning, transformation, and normalization of data.
6. Testing the classical assumptions of regression.
7. Construction of Multiple Linear Regression model.
8. Construction of a Random Forest Regressor model.
9. Construction of the Gradient Boosting Regressor model.
10. Model evaluation using MAE, RMSE, and R2
11. Model performance comparison.
12. Interpretation of results and drawing conclusions

2.2.Data Acquisition

The research data was obtained using a survey method by distributing questionnaires to respondents within the University of Batam. The sampling technique used purposive sampling, considering respondents who actively use the campus academic and administrative information systems. The research instrument used a 1–5 Likert scale with indicators adapted from the concepts of information technology use, digital competence, and the effectiveness of management information systems. The obtained primary data were then processed using the Python programming language with the Pandas, Scikit-Learn, Statsmodels, and NumPy libraries.

2.3.Data Analysis Technique

Multiple linear regression is used to measure the influence of IT Usage and Digital Competence on Management Information Systems. The regression equation model is Y=a+b1X1+b2X2+e.

Information:
Y = Management Information System
a= constant
b_1, b_2= regression coefficient
X_1= Use of IT
X_2= Digital Competence
e= error

Linear regression is used because it is able to explain the cause-effect relationship between variables empirically and is still the main method in information systems research.[8].

2.4.Machine Learning Models

Random Forest is a decision tree-based ensemble learning algorithm that works by building multiple decision trees to improve prediction accuracy and reduce overfitting. This method is effective in handling complex data and non-linear relationships between variables.[3]Gradient Boosting is a boosting algorithm that builds a predictive model gradually by correcting the errors of the previous model using gradient descent optimization. This method is known for its high performance in predictive analytics.[9].

2.5.Model Evaluation

After training the model using training data, the next stage is model evaluation using testing data to measure the predictive capability of the Management Information System based on IT Usage and Digital Competence variables. The evaluation is conducted using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R2).[10]MAE is used to measure the average prediction error, RMSE to determine the model error level, and R2 to measure the model's ability to explain variations in actual data. The smaller the MAE and RMSE values and the larger the R2 value, the better the model performance. This evaluation is used to compare the performance of Multiple Linear Regression, Random

Forest Regressor, and Gradient Boosting Regressor in predicting the Management Information System of Batam University.

2.5.1.Mean Absolute Error (MAE)

MAE is used to measure the average absolute error of a model's predictions. The smaller the MAE value, the closer the predicted results are to the actual observed values.[10].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_i}| \tag{1}$$

2.5.2.Root Mean Square Error (RMSE)

The RMSE is used to measure the error rate of a model based on squared residuals. A low RMSE value indicates a more accurate prediction, and the best value is close to zero. The RMSE is calculated by taking the square root of the MSE. A low RMSE indicates a very accurate error estimation method.[10].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \tag{2}$$

2.5.3.Coefficient of Determination (R2)

R^2 is an indicator that shows a model's ability to explain data variation. It is used to measure the model's ability to explain data variation. The closer the R^2 value is to 1, the better the model is at explaining the data, with values ranging from 0 to 1.[10].

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{3}$$

The smaller the MAE and RMSE values and the larger the R2 value, the better the model is considered to have predictive performance.[11]

2.5.4.Result Prediction

The result prediction stage is carried out after the Multiple Linear Regression, Random Forest Regressor, and Gradient Boosting Regressor models have been trained using the training data. At this stage, the model is used to predict the value of the Management Information System based on the IT Usage and Digital Competence variables in the testing data. The prediction results are then compared with the actual data to determine the level of accuracy and generalization ability of the model. The prediction process is carried out using the Scikit-Learn library in Python with a supervised learning approach. Model performance evaluation is carried out using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination () because these metrics are considered effective in measuring the level of prediction error and the model's ability to explain the variability of the actual data. Smaller MAE and RMSE values indicate a lower level of prediction error, while higher values indicate a better model's ability to explain the data. The model with the lowest MAE and RMSE values and the highest values is selected as the best model in predicting the Management Information System of Batam University.$R^2R^2R^2$[12][13]

2.5.5.Data Visualization

The data visualization stage is carried out to facilitate the interpretation of the results of regression analysis and machine learning. Data visualization is used to display patterns of relationships between variables, data distribution, model prediction results, and comparisons of the performance of algorithms used in the study. Visualization is done using graphs and plots such as regression plots, actual vs. prediction plots, and comparison charts for MAE, RMSE, and . The visualization process is carried out using the Matplotlib and Seaborn libraries in Python so that the analysis results can be understood more clearly, informatively, and support data-based decision-making. Data visualization also plays a crucial role in helping interpret data patterns and improving understanding of machine learning model performance more effectively and interactively.R^2[14] [15].

3. Results and Discussion

3.1. Data Preprocessing Results

The preprocessing stage was conducted before the modeling process to ensure the quality of the data used in the study. This process included data cleaning, handling missing values, data transformation, feature selection, and dividing the data into training and testing datasets with an 80:20 ratio. The variables used in the study consisted of IT Usage (X1), Digital Competence (X2), and Management Information Systems (Y). After preprocessing, the dataset was declared ready for use in linear regression and machine learning processes.

3.2. Classical Assumption Testing

3.3.1. Normality Test

The normality test was conducted using the Shapiro-Wilk method to determine whether the residuals of the regression model were normally distributed. The test results showed a statistical value of 0.9937 with a p-value of 0.8724. Because the p-value is greater than 0.05, the residuals are declared normally distributed, thus the normality assumption in the regression model has been met. The Shapiro-Wilk test is one of the methods widely used in statistical analysis because it has a good level of sensitivity and accuracy in detecting normal distribution in small and medium sample sizes.[16].

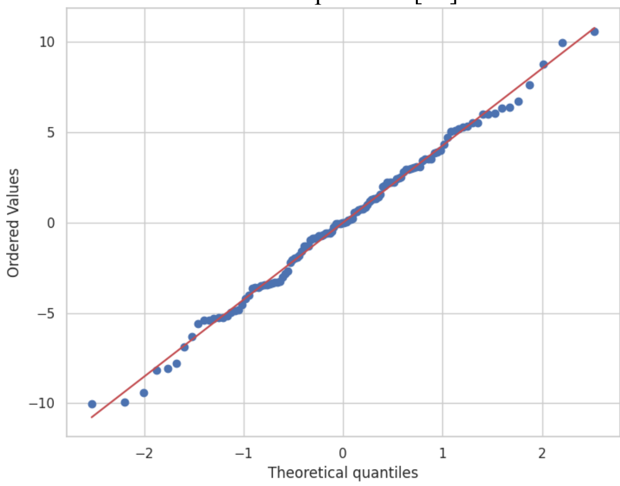

Figure 1. Normal QQ Plot (Residual Normality)

In Figure 1 of this Normal QQ Plot, the X-axis shows the theoretical quantiles of the normal distribution, while the Y-axis shows the quantiles of the sample residuals. The points on the plot appear to follow a straight diagonal line even though the reference line is not explicitly drawn. There are no systematic patterns such as S-shapes or extreme curvatures. Some points at the tail end of the distribution show slight deviations, but overall they are still within reasonable limits. Based on this pattern, it can be concluded that the model residuals approach a normal distribution, so the assumption of normality in the statistical analysis is met.

Methodologically, the Normal Q–Q Plot is used to compare the empirical residual quantiles with the theoretical quantiles of the normal distribution to visually evaluate the assumption of normality. Methodologically, the fit of the distribution is indicated by a pattern of points that approximates a straight line, while deviations from linearity, particularly in the tails, indicate potential distributional misfit.[17].

In statistical interpretation, a linear pattern in a Q–Q plot indicates that the residuals are approaching a normal distribution, while a curved, S-shaped pattern, or extreme deviations in the tails indicate a violation of the assumption. However, recent studies suggest that small deviations in the tails can still occur naturally due to sampling variation, especially in observational data or with limited sample sizes.[18][19]Based on the pattern showing residual points following a diagonal line with slight deviations in the tails, it can be concluded that the model residuals approach a normal distribution. Thus, the assumption of normality in statistical analysis can be considered practically fulfilled.

3.3.2. Autocorrelation Test

The autocorrelation test was conducted using the Durbin-Watson method to determine the residual correlation between observations in the regression model. The test results showed a Durbin-Watson value of 1.6897. This value is close to 2, thus it can be concluded that the regression model does not experience serious autocorrelation and the residuals between observations are independent. The Durbin-Watson test is widely used in regression analysis because it is effective in detecting serial relationships in residuals and ensuring that the regression model meets the assumption of error independence.[20].

3.3.3. Heteroscedasticity Test

Heteroscedasticity testing was performed using the Breusch-Pagan and White Test methods. The Breusch-Pagan results showed a statistical value of 2.7686 with a p-value of 0.2505, while the White Test produced a statistical value of 7.8928 with a p-value of 0.1622. Because both p-values are greater than 0.05, the regression model does not experience heteroscedasticity.

3.3.4. Multicollinearity Test

An autocorrelation test was performed using Durbin-Watson to determine the residual correlation between observations. The test results showed a Durbin-Watson value of 1.6897. This value is close to 2, thus concluding that the model does not experience serious autocorrelation.

3.2. Multiple Linear Regression Results

The results of the multiple linear regression parameter estimation obtained the following equation:
Y=14.5118+0.4579X1+0.4205X2

Based on the regression results, the IT Usage variable has a coefficient of 0.4579 with a significance value of 0.000 <0.05. This indicates that IT Usage has a positive and significant effect on Management Information Systems. The Digital Competence variable has a coefficient of 0.4205 with a significance value of 0.000 <0.05, which means that Digital Competence also has a positive and significant effect on Management Information Systems. The coefficient of determination (R2) value of 0.8740 indicates that 87.40% of the variation in Management Information Systems can be explained by IT Usage and Digital Competence, while the remaining 12.60% is influenced by other variables outside the study. In addition, the F-statistic probability value of 2.3169e-53 indicates that the regression model is simultaneously significant and suitable for use in research.

3.3. Machine Learning Model Evaluation

Machine learning model evaluation was performed using MAE, RMSE, and Score on the testing data. The evaluation results are shown in the following table.R^2.

Table 1. Machine Learning Model Evaluation

Model	MAE	RMSE	R^2 Score
Multiple Linear Regression	3.136370	3.702365	0.894145
Random Forest Regressor	2.808244	3.506074	0.905072
Gradient Boosting Regressor	3.070617	3.632077	0.898126

Based on the evaluation results, Random Forest Regressor produced the best performance compared to other models with the lowest MAE and RMSE values and the highest value of 0.905072. These results indicate that Random Forest has better predictive ability in modeling the Management Information System of Batam University. Meanwhile, Multiple Linear Regression still shows good performance with a value of 0.894145 and has the advantage of interpreting relationships between variables that are easier to understand statistically. Gradient Boosting Regressor also shows high performance, but still slightly below Random Forest Regressor. These results indicate that the Random Forest algorithm has the best predictive ability in modeling the Management Information System of Batam University.$R^2 R^2$

3.4. Discussion

The results of the study indicate that IT utilization and digital competence have a positive and significant impact on the Management Information System at Batam University. This finding suggests that the higher the level of information technology utilization and digital competence of users, the greater the effectiveness of the Management Information System implementation. Optimal use of information technology enables faster, more efficient, and more accurate administration, data management, organizational communication, and decision-making processes. This finding supports the research.Saltos-rivas, Novoa-herna, & Rodrıguez (2021)which explains that digital competence is an important factor in the effectiveness of technology implementation in higher education environments.

The results of this study are also in line with researchSukorini, Marini, & Aulia (2024)which states that digital transformation in higher education requires integration between information technology, human resource competencies, and management information systems that are adaptive to digital technology developments. In addition, researchSetyadi, Pawirosumarto, Damaris, & Dharma (2025)explains that digital technology literacy has a significant contribution to improving the performance of learning innovation and the effectiveness of technology-based higher education management.

From a machine learning perspective, the research results show that Random Forest Regressor has a better predictive accuracy rate than Multiple Linear Regression and Gradient Boosting Regressor. This demonstrates that the ensemble learning approach is able to handle complex and non-linear data relationships more effectively than conventional statistical models. These findings support researchFan & Chiong (2023)which states that the machine learning approach has high capability in identifying digital capability patterns in the higher education environment.

This research also strengthens researchQuttainah & Singh (2024)which explains that the strategy for developing digital competencies in educational organizations is a crucial factor in the success of digital transformation and the development of modern information systems. In addition, researchDang, Phan, Vu, La, & Pham (2024)Digital competence of lecturers and its impact on student learning value in higher education shows that digital competence has a significant impact on the quality of learning and the effectiveness of technology use in higher education.

The high R2 values across all models indicate that IT Usage and Digital Competence are important variables in predicting the Management Information System of Batam University. These results indicate that the implementation of modern information systems in higher education is not only dependent on technological infrastructure but is also influenced by the readiness of users' digital competence in optimally utilizing technology.Sari, Habibi, & Hendra (2025)also explains that the technology-based educational environment is greatly influenced by the quality of academic services and the digital capabilities of users in utilizing information technology systems.

Overall, this study demonstrates that the integration of statistical regression and machine learning approaches can produce an accurate and adaptive Management Information System prediction model. This research provides theoretical contributions to the development of machine learning-based information systems studies in higher education and provides practical contributions to Batam University in supporting data-driven decision-making and strengthening the institution's digital transformation.

4. Conclusion

This study successfully built a prediction model of the Management Information System of Batam University using the Multiple Linear Regression, Random Forest Regressor, and Gradient Boosting Regressor approaches based on the variables of IT Usage and Digital Competence. The results of the classical assumption test indicate that the regression model meets the assumption of normality, does not experience serious autocorrelation, heteroscedasticity, or multicollinearity so that the model is suitable for use in research. The results of the linear regression show that IT Usage and Digital Competence have a positive and significant effect on the Management Information System with a coefficient of determination of 87.40%, which indicates that both independent variables have a strong contribution in explaining the variability of the Management Information System at Batam University.

Based on the results of the machine learning evaluation, Random Forest Regressor produced the best performance compared to Multiple Linear Regression and Gradient Boosting Regressor with the lowest MAE and RMSE values and the highest R2 value of 0.905072. These results indicate that the Random Forest algorithm has better predictive capabilities in modeling digital data-based Management Information Systems. This study proves that the integration of statistical regression and machine learning approaches can produce accurate and effective predictive models in supporting the management of higher education information systems. In addition to providing theoretical contributions to the development of machine learning-based information system research, this study also provides practical contributions to Batam University in supporting data-based decision making and strengthening the digital transformation of higher education institutions.

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