INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

Web-Based Boarding House Management Information System with Dashboard Analytics and Multiple Linear Regression for Rental Income Prediction

Riky Fauzan*, Syarif Hidayatulloh

Information Systems Study Program, Faculty of Information Technology, Universitas Adhirajasa Reswara Sanjaya, Bandung, Indonesia

DOI: https://doi.org/10.51583/IJLTEMAS.2026.150600293

Received: 18 July 2026; Accepted: 23 July 2026; Published: 04 August 2026

ABSTRACT

Small boarding-house businesses commonly rely on receipts and annual notebooks to record tenants, rental periods, payments, unit availability, and income. Such practices can support daily operations, but they make historical retrieval, operational monitoring, and decision support increasingly difficult as the number of records grows. This study develops a web-based boarding house management information system that integrates operational data management, dashboard analytics, and rental-income prediction for Surapati Boarding House in Bandung, Indonesia. The application was developed with Laravel 12, PHP, and MySQL, while the predictive model was trained offline in Python using scikit-learn. Because the original tenant and payment records contain private information, a simulated historical dataset was constructed from the property's operational characteristics. The dataset contains 54 monthly observations from January 2022 to June 2026. The independent variables were occupied Type A units, occupied Type B units, and payment arrears, while monthly rental income was the dependent variable. After cleaning currency-formatted values and removing invalid rows, the data were divided into 43 training observations and 11 testing observations. The resulting multiple linear regression model was integrated into the Laravel analytics page through its estimated intercept and coefficients. The system provides authentication, unit and tenant master data, rental transactions, payment records, operational summaries, due-date reminders, and an analytics interface that compares actual and predicted income. Model evaluation produced an R-squared value of 95.85%, a mean absolute error of IDR 250,715.83, a root mean squared error of IDR 303,605.01, and a mean absolute percentage error of 1.39%. These results indicate close agreement between predicted and simulated actual income. However, the findings are limited to the simulated case-study dataset and require validation using anonymized real operational data before broader deployment.

Keywords: boarding house management system, dashboard analytics, multiple linear regression, rental income prediction, web application

INTRODUCTION

Boarding-house management involves tenant registration, unit availability monitoring, rental-period administration, payment recording, and income reporting. When these activities are handled through receipts and handwritten notebooks, information can be scattered across documents and retrieving older records becomes time-consuming. Web-based information systems have therefore been applied to boarding-house administration to centralize tenant, unit, transaction, and payment data [2], [3], [5], [10], [13].

Surapati Boarding House is a small rental business in Bandung that manages 12 rental units: five Type A units with two bedrooms and seven Type B units with one bedroom. The owner previously recorded tenant identities and payments using receipts and annual notebooks. Although the manual process remained usable, it became difficult to retrieve records from several years earlier and to obtain a rapid overview of unit occupancy, due dates, arrears, and income trends.

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A dashboard can summarize operational information through key indicators and visualizations, allowing managers to understand conditions without reviewing every transaction individually. Prior research has shown that well-designed dashboards can improve access to operational insights and support decision-making [1], [6], [14]. In addition, historical operational data can be used to estimate future or scenario-based income through regression models [4], [11].

Previous boarding-house systems have largely focused on digital administration, tenant records, payments, complaints, and unit information [2], [3], [5], [10], [13]. The contribution of this study is the integration of management functions, dashboard analytics, and a multiple linear regression module in one web application. The study aims to (1) develop an integrated web-based management system, (2) provide concise operational analytics, and (3) implement and evaluate an income-prediction model using the available case-study variables.

Related Work

Setiawan et al. developed a web-based boarding-house information system to support rental data management [13]. Basir and Saifudin similarly reported a web system for boarding-house information and administration [3], while Hasti and Zaelani implemented website-based tenant, complaint, and payment management [5]. These studies demonstrate the operational value of digitization but do not combine administrative functions with predictive income analytics.

Nugraheny et al. applied multiple linear regression in a web-based minimum-income prediction application [11], and Fadianty used multiple linear regression to predict sales turnover from historical data [4]. These studies support the use of regression for numeric business prediction. The present study adapts the approach to a small boarding-house context and integrates model outputs into a Laravel dashboard.

METHODOLOGY

Research design and system development

The study used a case-study and prototype-oriented system-development approach. Requirements were collected through observation of the existing administrative process and interviews with the boarding-house owner. The prototype model was selected because screen layouts and workflows could be evaluated and refined against the owner’s operational needs [9].

The application was implemented with Laravel 12 using the Model-View-Controller architecture, PHP for server-side processing, MySQL for persistent storage, and Laragon as the local development environment. The system contains authentication, rental-unit master data, tenant master data, rental transactions, payments, an operational dashboard, and an analytics report. Laravel’s framework structure was used to separate business logic, views, and database interaction [8].

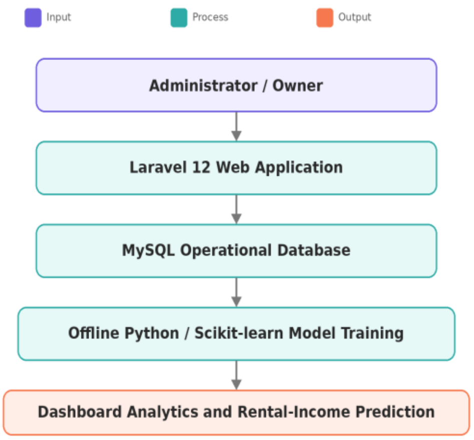

Figure 1: System architecture and offline prediction-model integration.

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Dataset and variables

Real tenant and payment records were not directly used because they contain personally identifiable information. Instead, a simulated historical dataset was generated from the boarding house's operational characteristics, including the fixed unit inventory, rental rates, occupancy changes, contract renewals, departures, new tenants, payment schedules, and arrears. The dataset contains 54 monthly observations covering January 2022 through June 2026.

Type A represents occupied two-bedroom rental units and Type B represents occupied one-bedroom rental units. The target variable is monthly rental income. Payment inflow was retained as operational information but was not selected as a predictor because tenants may pay three, six, or twelve months in advance, causing payment inflow to be zero in some months even when units remain occupied.

Table 1: Variables used in the multiple linear regression model.

Variable	Description	Role
X1	Number of occupied Type A units	Independent variable
X2	Number of occupied Type B units	Independent variable
X3	Payment arrears (IDR)	Independent variable
Y	Monthly rental income (IDR)	Dependent variable

Data preprocessing and model training

The spreadsheet contained currency values represented as text, such as "Rp14.750.000". Preprocessing removed empty header rows and fully empty records, standardized the column names, stripped currency symbols and thousands separators, converted numeric attributes to floating-point values, and removed rows with incomplete model variables. All 54 valid monthly observations were retained.

The data were divided into 43 training observations and 11 testing observations using an 80:20 holdout split implemented with scikit-learn's train_test_split function (random_state = 42). A LinearRegression estimator was fitted using ordinary least squares, which minimizes the sum of squared residuals [7], [12]. Model training was performed offline in Python; the estimated intercept and coefficients were then inserted into the Laravel analytics controller for real-time scenario calculations.

$$\mathbf{\hat{Y} = a + b_1X_1 + b_2X_2 + b_3X_3}$$

Evaluation metrics

Prediction performance was evaluated on the testing set using the coefficient of determination (R^2), mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE). R^2 measures the proportion of variation explained by the model, MAE reports the average absolute error in rupiah, RMSE gives greater weight to large errors, and MAPE expresses average absolute error as a percentage.

RESULTS

System implementation

The implemented application centralizes data that were previously recorded in separate paper documents. The main dashboard displays monthly income, occupied and available units, units under maintenance, recent income trends, and upcoming rental due dates. Master-data pages allow the administrator to manage units and tenants, while operational pages record rental agreements and payments.

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The interface was designed for a single administrator role representing the owner or manager. Functional verification was performed for login, data creation and editing, rental transactions, payment recording, dashboard summaries, and prediction calculations.

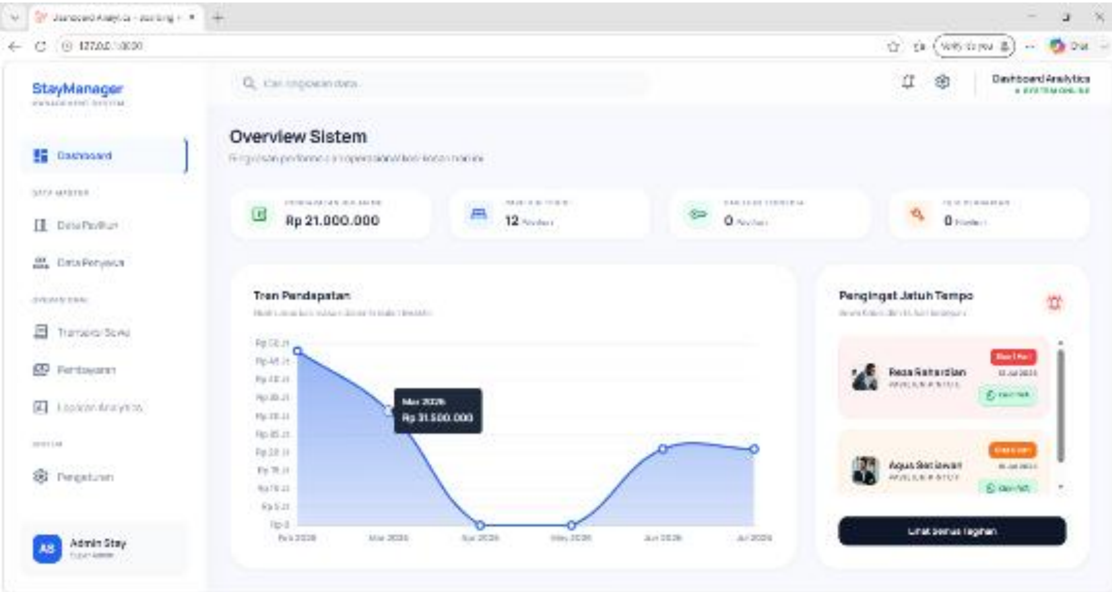

Figure 2: Main operational dashboard of the boarding-house management system.

Regression model

The trained model produced the parameters shown in Table 2. The negative arrears coefficient indicates that, while Type A and Type B occupancy are held constant, an increase of IDR 1,000,000 in arrears is associated with an estimated decrease of approximately IDR 63,490 in recognized monthly income.

Table 2: Estimated multiple linear regression parameters.

Parameter	Estimated value
Intercept (a)	2,306,841.69
Type A coefficient (b1)	2,309,775.01
Type B coefficient (b2)	1,098,862.53
Arrears coefficient (b3)	−0.063490

$$\hat{Y} = 2{,}306{,}841.69 + 2{,}309{,}775.01X_1 + 1{,}098{,}862.53X_2 - 0.063490X_3$$

Prediction results

Table 3 presents the complete 11-observation testing set in chronological order. The absolute difference between actual and predicted income ranges from IDR 51,108.10 to IDR 600,029.37.

Table 3: Actual and predicted income on the testing set (IDR).

Period	Actual income	Predicted income	Absolute error
Apr-2022	16,750,000.00	17,040,254.37	290,254.37
Jun-2022	16,750,000.00	17,040,254.37	290,254.37
Jan-2023	18,500,000.00	18,139,116.90	360,883.10
Feb-2023	18,500,000.00	18,139,116.90	360,883.10

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Jun-2023	18,750,000.00	19,350,029.37	600,029.37
Aug-2023	16,750,000.00	17,040,254.37	290,254.37
Sep-2024	18,500,000.00	18,139,116.90	360,883.10
Sep-2025	20,500,000.00	20,448,891.90	51,108.10
Jan-2026	20,500,000.00	20,448,891.90	51,108.10
Feb-2026	20,500,000.00	20,448,891.90	51,108.10
May-2026	20,500,000.00	20,448,891.90	51,108.10

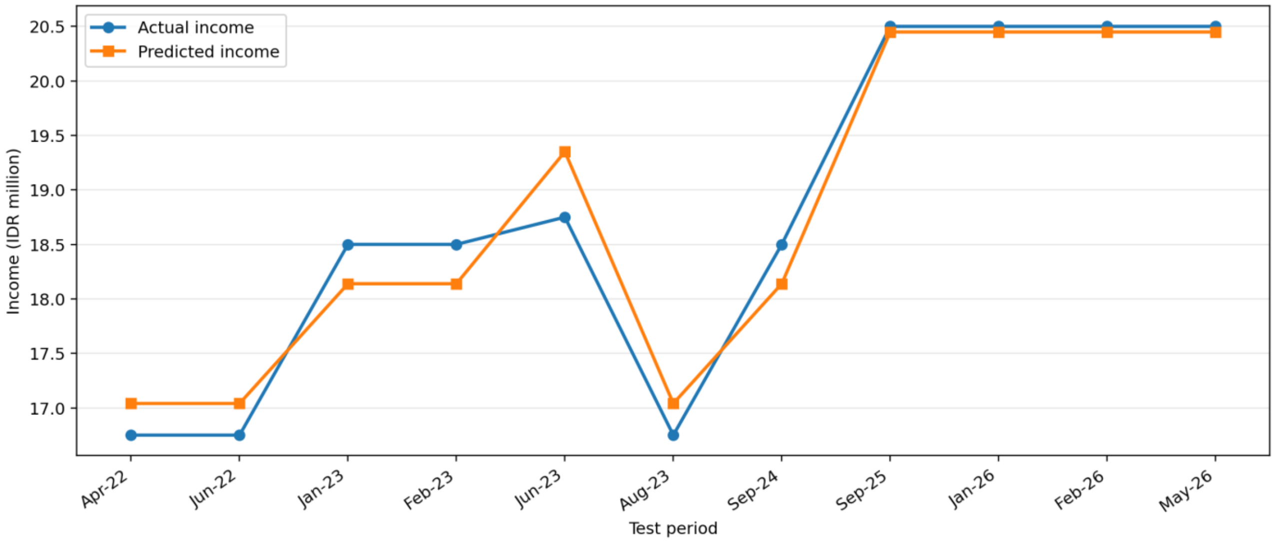

Figure 3: Comparison of actual and predicted income for the testing observations.

Model evaluation

Table 4: Model evaluation results.

Metric	Result
R^2	95.85%
MAE	IDR 250,715.83
RMSE	IDR 303,605.01
MAPE	1.39%

The R^2 score indicates that the model explains 95.85% of the variation in the testing data. The MAPE of 1.39% indicates a low relative error for the simulated dataset, while MAE and RMSE show that the average monetary deviation is small relative to monthly income values of approximately IDR 14.75–20.50 million.

Analytics-dashboard integration

The analytics page presents R^2, MAPE, the number of historical observations, a prediction simulator, and a comparison chart. Users enter occupied Type A units, occupied Type B units, and arrears; the page calculates income using the stored regression parameters. For example, five occupied Type A units, six occupied Type B units, and no arrears produce an estimated income of approximately IDR 20.45 million.

The prediction module uses offline training rather than calling Python as a live service. This reduces deployment complexity for a small local application, although retraining requires rerunning the Python script and updating the stored parameters.

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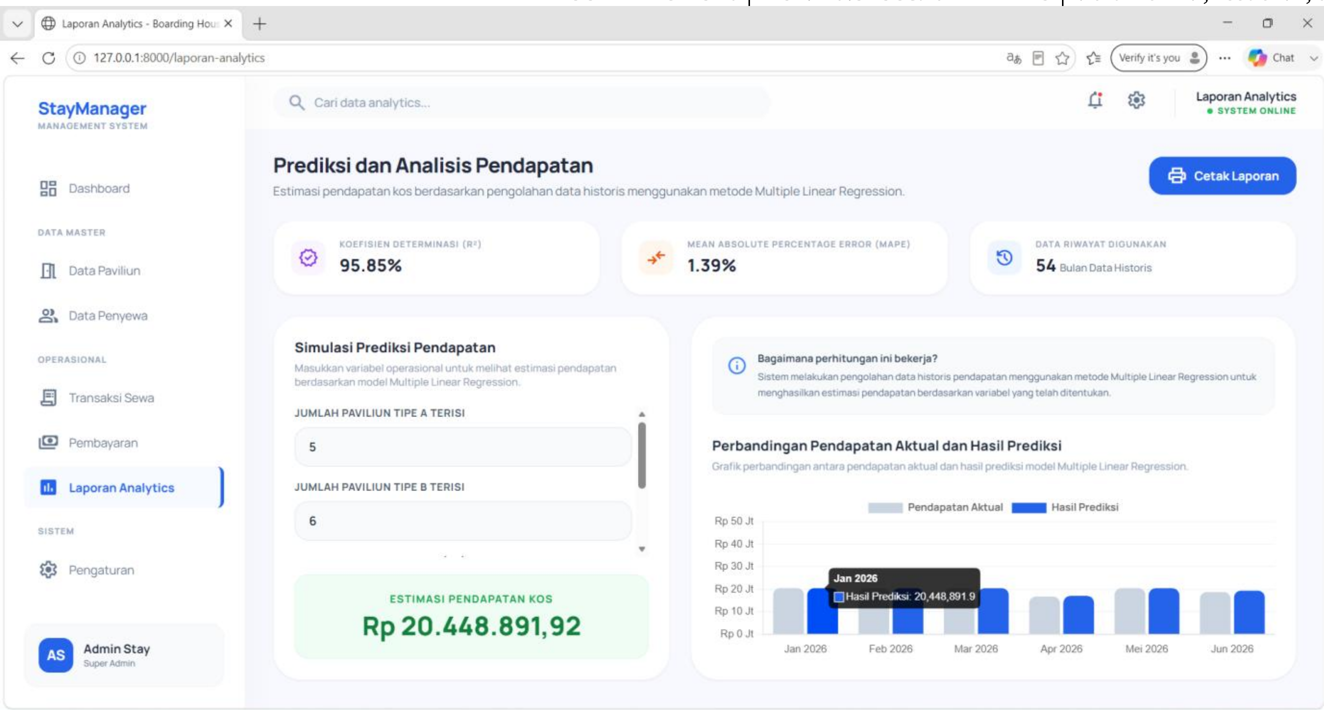

Figure 4: Integrated prediction and analytics page showing model metrics and scenario-based income estimation.

DISCUSSION

The developed system extends earlier boarding-house applications by combining administrative management, operational visualization, and numeric income prediction in a single application. Where prior studies primarily addressed tenant data, payments, and unit information [2], [3], [5], [10], [13], the present implementation adds an analytics page that exposes model performance and allows scenario-based estimates.

The dashboard condenses operational data into cards, reminders, and charts. This design is consistent with research emphasizing that dashboards should provide actionable information rather than reproduce raw transactional records [6], [14]. For the case-study owner, the integrated view reduces the need to search annual notebooks to determine occupancy, upcoming due dates, or income trends.

The regression results demonstrate close numerical agreement on the simulated testing set. However, the high R^2 and low MAPE must be interpreted cautiously. The dataset was constructed from a fixed inventory and known rental-price structure; occupied Type A and Type B units are therefore direct drivers of monthly income. Consequently, the model primarily captures the internal logic of the simulation rather than unexpected market behavior. The findings establish that the implementation pipeline works, but they do not prove equivalent predictive accuracy on real-world data.

The inclusion of arrears provides an operational adjustment, but additional predictors such as maintenance downtime, price changes, seasonality, contract renewal probability, and actual anonymized cash-flow timing could improve realism. A chronological holdout or rolling time-series evaluation should also be considered in future work to better represent deployment in which earlier periods predict later periods.

The offline integration strategy is practical for a small boarding-house system because it avoids maintaining a separate Python web service. Its limitation is that the model does not update automatically when new records are added. A future version could store model metadata in MySQL, trigger scheduled retraining, and preserve model versions for auditability. Future implementation may further improve adaptability by applying automated retraining schedules and storing updated model artifacts within the database environment.

The current evaluation should be interpreted as an initial feasibility assessment because the model validation was performed using a simulated dataset derived from a single boarding-house case study. Future validation

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using anonymized real-world rental transactions and additional external variables, such as seasonal demand changes and maintenance conditions, is required to assess broader generalization performance.

CONCLUSION

This study developed a web-based boarding-house management information system for Surapati Boarding House using Laravel 12 and MySQL. The application integrates unit and tenant data, rental transactions, payments, operational summaries, due-date reminders, and analytics in one interface.

A multiple linear regression model was trained in Python using 54 monthly simulated observations. Occupied Type A units, occupied Type B units, and payment arrears were used to estimate monthly rental income. On the 11-observation testing set, the model achieved R^2 of 95.85%, MAE of IDR 250,715.83, RMSE of IDR 303,605.01, and MAPE of 1.39%. The estimated parameters were successfully embedded in the Laravel analytics page for interactive scenario calculations.

The system demonstrates a feasible approach to combining operational information management and lightweight predictive analytics for a small rental business. Because the evaluation used simulated data derived from the case-study structure, future research should validate the model with anonymized real transactions, use time-aware validation, and compare multiple prediction methods before operational decisions rely on its estimates.

Data Availability

The dataset used in this study is a simulated monthly dataset based on the operational characteristics of the case-study boarding house. It does not contain identifiable tenant information. The processed dataset and Python analysis script may be obtained from the corresponding author upon reasonable request.

Conflict of Interest

The authors declare no conflict of interest.

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