The IJICS (International Journal of Informatics and Computer Science)
Vol 10 No 2, July 2026, Page 185-190
ISSN 2548-8384 (online), ISSN 2548-8449 (print)
Available Online at https://ejurnal.stmik-budidarma.ac.id/index.php/ijics/index
DOI 10.30865/ijics.v10i2.9859

Laundry Performance Analysis Using KPI and Linear Regression Dashboard

Dameria E Br Jabat*, Megaria Purba, Putri D Br Sitorus, Eva S Saragih
[1] Information Technology. STMIK Pelita Nusantara, Medan, Indonesia
Email: [1] *sijabatdame@gmail.com, [2] Megariapurna18@gmail.com, [3]putridianasitorus65@gmail.com, [4]evasaragih264@gmail.com
(* : sijabatdame@gmail.com)
Submitted: **29/06/2026**; Accepted: **20/07/2026**; Published: **29/07/2026**

Abstract−This study develops an integrated approach for measuring and forecasting the revenue performance of a small laundry business using Key Performance Indicators (KPIs), simple linear regression, and a dashboard prototype. The dataset consists of operational records from one Indonesian laundry enterprise covering January–June 2024. Daily records were validated, anonymized, and aggregated into six monthly observations containing transaction volume, customer count, laundry weight, revenue targets, and actual revenue. The KPIs comprised total revenue, month-to-month revenue growth, average revenue per transaction, and target achievement. A chronological holdout was used to evaluate the regression model: January–April formed the training set, whereas May–June formed the test set. The holdout evaluation produced MAE of Rp1,287,500, RMSE of Rp1,319,209, and MAPE of 6.31%. After validation, the model was refitted to all six observations, resulting in $\hat{Y} = 13{,}216{,}666.67 + 1{,}235{,}714.29X$ with $R^2 = 0.9198$. Total observed revenue was Rp105,250,000; the highest monthly revenue was Rp21,000,000 in June; average revenue per transaction remained Rp50,000; and overall target achievement was 105.25%. The model forecast revenues of Rp21.87 million, Rp23.10 million, and Rp24.34 million for July, August, and September, respectively. The dashboard consolidates the KPI and forecast results into a concise decision-support view. Because the analysis uses one business and only six monthly observations, the forecasts should be interpreted as an exploratory trend estimate rather than a generalizable long-term model.

Keywords: Business Intelligence; Dashboard; Key Performance Indicator; Linear Regression; Revenue Forecasting; Small Business

1. INTRODUCTION

Small and medium-sized enterprises increasingly generate transaction data but often lack the analytical resources required to convert those records into actionable information. Research on Business Intelligence and Analytics (BI&A) in SMEs indicates that adoption remains uneven, even though systematic use of data can improve performance monitoring and managerial decision-making [1], [2]. The issue is particularly relevant to service businesses, where revenue depends on recurring operational activity and where managers frequently rely on manually prepared summaries.

Business Intelligence creates value when data are transformed into information that supports organizational processes and decisions [3]. Performance measurement is one practical use of BI. Key Performance Indicators (KPIs) translate business objectives into measurable results, while BI systems can strengthen performance measurement capabilities when indicators are aligned with managerial needs [4]. For a laundry business, revenue, transactions, customers, average transaction value, revenue growth, and target achievement provide a compact representation of commercial performance.

Dashboards are commonly used to present KPIs because they consolidate relevant measures, trends, and exceptions in a single visual interface [5]. Effective dashboards should not merely display large amounts of data; they should organize information according to the user's decision context and support rapid interpretation [6]. Empirical research also suggests that operational managers obtain greater value from dashboards when the displayed KPIs are specifically tailored to their responsibilities and strategic priorities [7].

Descriptive indicators explain what has occurred, but planning also requires an estimate of what may occur next. Linear regression provides an interpretable baseline for modeling a trend between a predictor and a response variable. Its transparency makes it useful in small-business settings where model outputs must be understandable to non-technical users. Nevertheless, predictive value depends on appropriate validation, and model fit on historical observations should not be treated as equivalent to performance on unseen data [10], [12].

Prior studies have examined BI adoption, dashboards, and analytical capability in SMEs [1], [2], [8], [9], but few studies integrate KPI measurement, an explicitly validated revenue-trend model, and a dashboard prototype for a micro-service context using a single consistent dataset. This study addresses that gap by: (1) measuring laundry revenue performance using operational KPIs; (2) evaluating a simple linear regression model with a chronological holdout; (3) forecasting the subsequent three months after refitting the model to all available observations; and (4) consolidating the results in a dashboard prototype. The contribution is an auditable, lightweight analytical workflow suitable as a proof of concept for small service enterprises.

2. RESEARCH METHODOLOGY

2.1 Research Design and Data Source

The study uses a quantitative case-study design with descriptive and predictive components. The descriptive component evaluates business performance through KPIs, whereas the predictive component estimates the monthly revenue trend using simple linear regression. The unit of analysis is one laundry SME in Indonesia. The dataset covers six consecutive months, from January to June 2024, and was obtained from operational transaction documentation and clarification interviews with the business owner.

The variables retained for analysis were month index, number of transactions, number of customers, laundry weight in kilograms, monthly revenue target, and actual monthly revenue. Customer names, telephone numbers, and other

The IJICS (International Journal of Informatics and Computer Science)
Vol 10 No 2, July 2026, Page 185-190
ISSN 2548-8384 (online), ISSN 2548-8449 (print)
Available Online at https://ejurnal.stmik-budidarma.ac.id/index.php/ijics/index
DOI 10.30865/ijics.v10i2.9859

personal identifiers were excluded. The data were used only in aggregate form. The limited period was retained rather than artificially expanding the dataset; consequently, the statistical analysis is treated as exploratory.

2.2 Data Preprocessing and Analytical Workflow

The preprocessing stage consisted of checking duplicate records, missing values, invalid dates, inconsistent numeric formats, and reconciliation between transaction totals and monthly revenue reports. Valid records were aggregated by month. The same cleaned monthly table was then used for KPI calculation, regression modeling, validation, forecasting, and dashboard visualization, thereby preventing inconsistencies between sections.

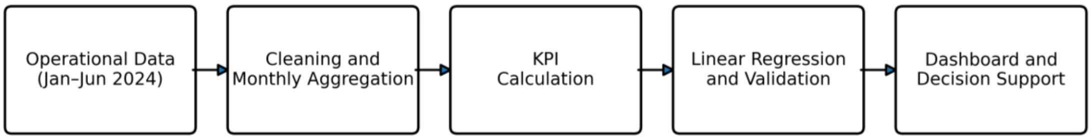

Fig 1. Research workflow for laundry revenue performance analysis

2.3 Key Performance Indicators

The selected KPIs were based on the variables available in the verified dataset. Total revenue measures accumulated income; revenue growth measures month-to-month change; average revenue per transaction measures transaction value; and target achievement compares actual revenue with the planned target. Transaction volume, customer count, and laundry weight are reported as supporting operational indicators. Customer retention and best-selling service were not calculated because repeat-customer identifiers and service-level revenue were not available; excluding these measures avoids unsupported claims.

$$TR = \Sigma_{t=1}^{n} R_t \quad (1)$$

$$RG_t = [(R_t - R_{t-1}) / R_{t-1}] \times 100\% \quad (2)$$

$$ART_t = R_t / T_t \quad (3)$$

$$TA_t = (R_t / G_t) \times 100\% \quad (4)$$

where TR is total revenue, R_t is actual revenue in month t, RG_t is revenue growth, ART_t is average revenue per transaction, T_t is the number of transactions, TA_t is target achievement, and G_t is the revenue target.

2.4 Linear Regression Model

Simple ordinary least squares regression was used to model monthly revenue as a function of time. The month index ($X = 1, \ldots, 6$) was the independent variable and actual monthly revenue was the dependent variable. The model is intended to represent a short-term linear trend; it does not estimate causal effects of transactions, customers, or promotions. Linear regression and its interpretation follow standard statistical-learning principles [12].

$$Y_t = a + bX_t + \varepsilon_t \quad (5)$$

$$b = [n\Sigma X_t Y_t - (\Sigma X_t)(\Sigma Y_t)] / [n\Sigma X_t^2 - (\Sigma X_t)^2] \quad (6)$$

$$a = \bar{Y} - b\bar{X} \quad (7)$$

$$R^2 = 1 - [\Sigma(Y_t - \hat{Y}_t)^2 / \Sigma(Y_t - \bar{Y})^2] \quad (8)$$

where Y_t is actual revenue, $\hat{Y}_t$ is predicted revenue, a is the intercept, b is the slope, ε_t is the residual, and R^2 is the coefficient of determination.

2.5 Validation, Forecast Accuracy, and Dashboard Verification

Forecast accuracy was assessed using a chronological holdout, which is preferable to evaluating only the same observations used to estimate the model [10]. The model was first trained on January–April and tested on May–June. After the holdout evaluation, it was refitted to all six months to produce the July–September forecasts. MAE and RMSE measure error in rupiah units, whereas MAPE provides a scale-independent percentage. Because MAPE has known limitations, it is reported together with absolute-error measures and only where actual revenue is strictly positive [10], [11], [15].

$$MAE = (1/m)\, \Sigma_{i=1}^{m} |Y_i - \hat{Y}_i| \quad (9)$$

$$RMSE = \sqrt{[(1/m)\, \Sigma_{i=1}^{m} (Y_i - \hat{Y}_i)^2]} \quad (10)$$

$$MAPE = (100\%/m)\, \Sigma_{i=1}^{m} |(Y_i - \hat{Y}_i) / Y_i| \quad (11)$$

The dashboard prototype was verified by reconciling each displayed KPI and forecast against the analytical tables. This verification tests numerical consistency, not usability. No formal user-acceptance or task-performance experiment was conducted.

3. RESULTS AND DISCUSSION

3.1 Research Data and KPI Results

Table 1 presents the consistent monthly dataset used throughout the study. The six-month period generated 2,105 transactions, served 1,261 recorded customers, processed 8,420 kg of laundry, and produced total revenue of Rp105,250,000 against a cumulative target of Rp100,000,000.

The IJICS (International Journal of Informatics and Computer Science)
Vol 10 No 2, July 2026, Page 185-190
ISSN 2548-8384 (online), ISSN 2548-8449 (print)
Available Online at https://ejurnal.stmik-budidarma.ac.id/index.php/ijics/index
DOI 10.30865/ijics.v10i2.9859

Table 1. Monthly operational and revenue data

Month	X	Transactions	Customers	Weight (kg)	Target (Rp)	Revenue (Rp)
January	1	310	185	1,240	15,000,000	15,500,000
February	2	295	176	1,180	15,000,000	14,750,000
March	3	330	198	1,320	16,000,000	16,500,000
April	4	360	215	1,440	17,000,000	18,000,000
May	5	390	235	1,560	18,000,000	19,500,000
June	6	420	252	1,680	19,000,000	21,000,000

Table 2. Monthly KPI results

Month	Revenue (Rp)	Growth (%)	Avg./Transaction (Rp)	Target Achievement (%)
January	15,500,000	–	50,000	103.33
February	14,750,000	-4.84	50,000	98.33
March	16,500,000	11.86	50,000	103.12
April	18,000,000	9.09	50,000	105.88
May	19,500,000	8.33	50,000	108.33
June	21,000,000	7.69	50,000	110.53

Revenue declined by 4.84% in February and then increased in every subsequent month. June recorded the highest revenue (Rp21,000,000) and the highest target achievement (110.53%). The average revenue per transaction remained exactly Rp50,000 in every month. Consequently, within this dataset, the increase in revenue was generated by higher transaction volume rather than by a change in the average transaction value. From January to June, revenue increased by 35.48%, while overall target achievement reached 105.25%.

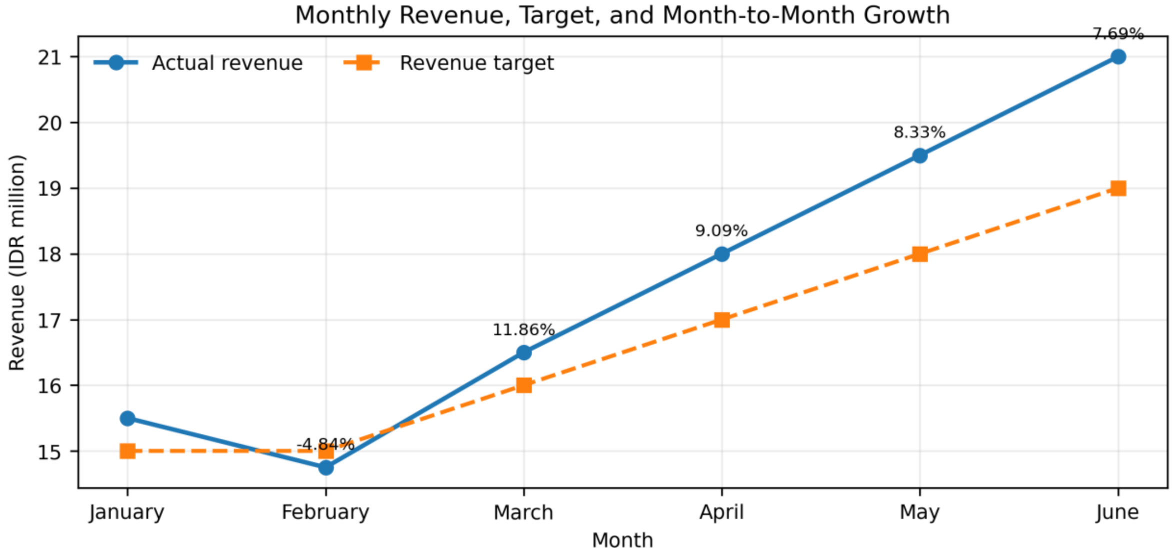

Fig 2. Monthly revenue, revenue target, and month-to-month growth

3.2 Linear Regression Validation and Forecast

The chronological holdout model estimated from January–April was $\hat{Y}$ = 13,875,000.00 + 925,000.00X. Table 3 compares its predictions with the two unseen months. The validation errors were MAE = Rp1,287,500.00, RMSE = Rp1,319,209.04, and MAPE = 6.31%. These values are less optimistic than the in-sample MAPE and therefore provide the primary indication of predictive performance.

Table 3. Chronological holdout validation results

Test Month	Actual Revenue (Rp)	Predicted Revenue (Rp)	Absolute Error (Rp)	APE (%)
May	19,500,000.00	18,500,000.00	1,000,000.00	5.13

The IJICS (International Journal of Informatics and Computer Science)
Vol 10 No 2, July 2026, Page 185-190
ISSN 2548-8384 (online), ISSN 2548-8449 (print)
Available Online at https://ejurnal.stmik-budidarma.ac.id/index.php/ijics/index
DOI 10.30865/ijics.v10i2.9859

June	21,000,000.00	19,425,000.00	1,575,000.00	7.50

After validation, the model was refitted using January–June. The resulting equation was $\hat{Y} = 13{,}216{,}666.67 + 1{,}235{,}714.29X$. The positive slope indicates an estimated average increase of Rp1,235,714.29 per month. The model explained 91.98% of the variation in the six observed monthly revenues ($R^2 = 0.9198$). Its in-sample MAE, RMSE, and MAPE were Rp507,142.86, Rp623,132.13, and 3.14%, respectively; these fit statistics are reported for completeness but should not replace the holdout results.

Table 4. Three-month revenue forecast with 95% prediction intervals

Month	X	Point Forecast (Rp)	Lower 95% PI (Rp)	Upper 95% PI (Rp)
July	7	21,866,666.67	18,971,668.78	24,761,664.56
August	8	23,102,380.95	19,872,287.19	26,332,474.71
September	9	24,338,095.24	20,732,665.74	27,943,524.74

The point forecasts increase from Rp21.87 million in July to Rp24.34 million in September. However, the prediction intervals widen as the forecast horizon extends. The intervals communicate that uncertainty is substantial relative to the short observation period and that the point forecasts should be used as planning ranges rather than guaranteed revenue levels.

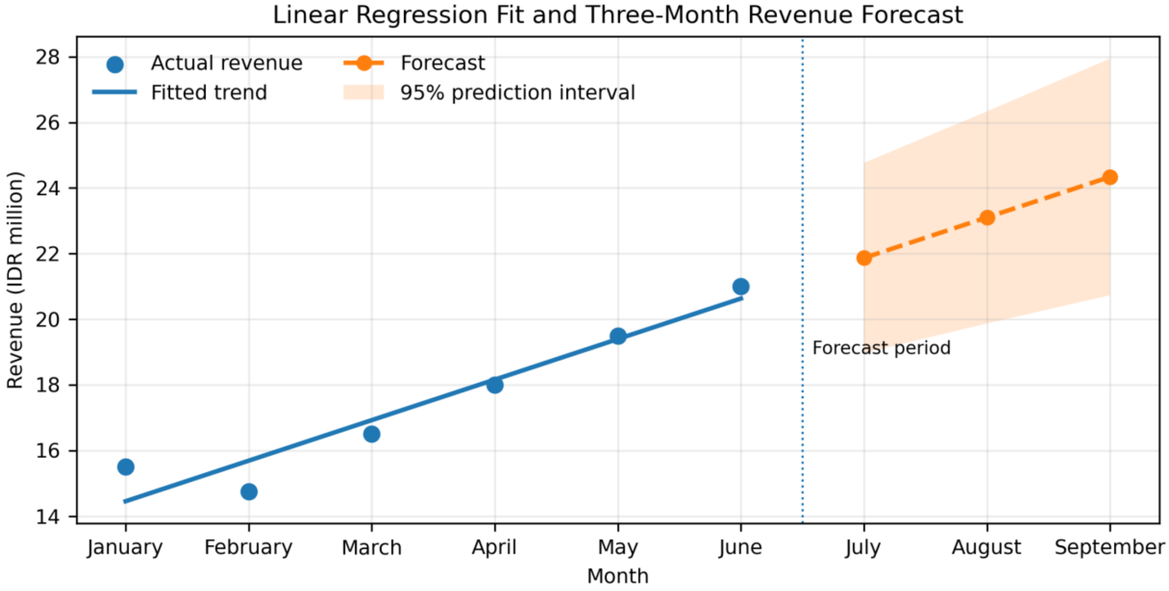

Fig 3. Linear regression fit, point forecasts, and 95% prediction intervals

3.3 Dashboard Prototype and Numerical Verification

Figure 4 presents the revised dashboard prototype. The upper cards summarize total revenue, overall target achievement, transaction and customer volumes, average revenue per transaction, and holdout MAPE. The supporting charts compare actual revenue with targets, display operational volume, highlight monthly growth, and distinguish historical observations from future forecasts. Every value shown in the dashboard was reconciled with Tables 1–4, and no numerical discrepancy was identified.

The IJICS (International Journal of Informatics and Computer Science)
Vol 10 No 2, July 2026, Page 185-190
ISSN 2548-8384 (online), ISSN 2548-8449 (print)
Available Online at https://ejurnal.stmik-budidarma.ac.id/index.php/ijics/index
DOI 10.30865/ijics.v10i2.9859

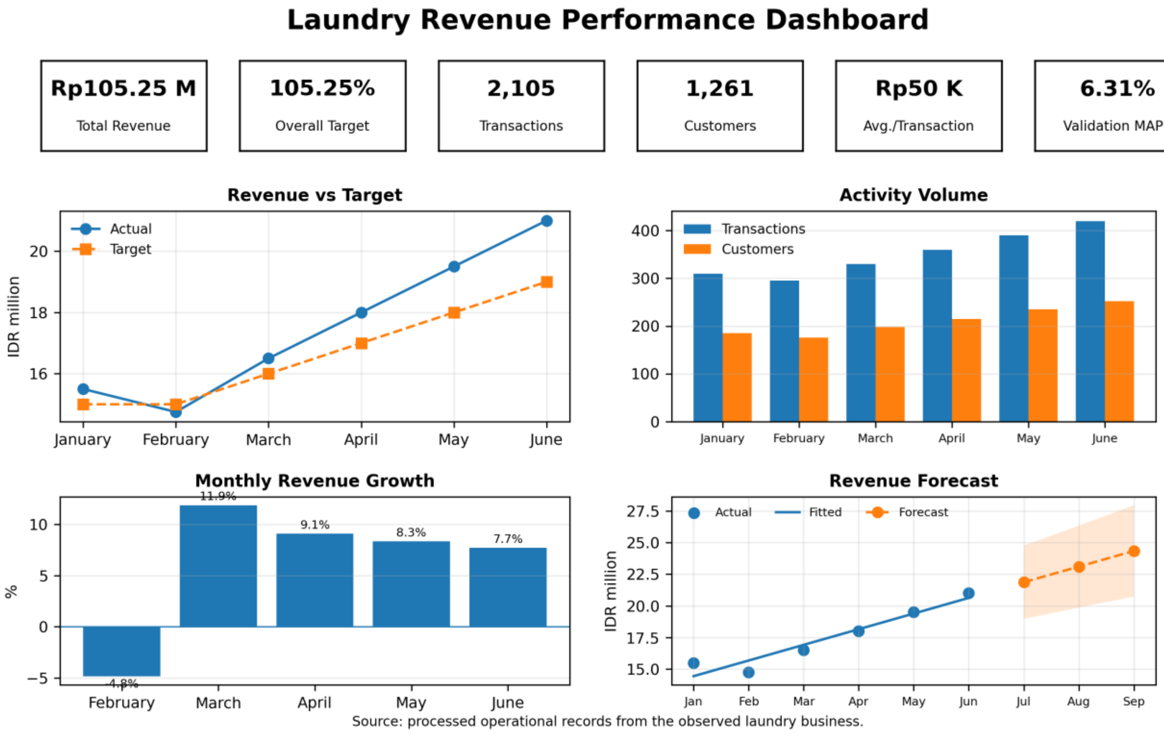

Fig 4. Business Intelligence dashboard prototype for KPI monitoring and revenue forecasting

The dashboard is a visual prototype based on the available dataset; it does not establish real-time integration with a transaction system. In an operational implementation, data refresh, user filters, access control, and usability testing would need to be added before deployment.

3.4 Discussion

The KPI results indicate a volume-driven revenue pattern. Because the average revenue per transaction was constant at Rp50,000, monthly revenue moved in direct proportion to transaction count. The February revenue decline coincided with lower transactions, customers, and laundry weight, whereas the March–June improvement coincided with increases in the same operational measures. This finding supports the managerial use of linked financial and operational KPIs rather than monitoring revenue alone. It does not, however, prove that customer count or laundry weight caused revenue growth, because the study did not estimate a multivariable causal model.

Target achievement rose from 98.33% in February to 110.53% in June. The persistent overachievement after March is favorable, but it also suggests that the target-setting process should be reviewed. A dashboard can make this pattern visible and enable managers to recalibrate future targets using recent operating capacity rather than retaining targets that become progressively easier to exceed. This interpretation is consistent with research showing that BI systems create greater value when analytical outputs are integrated into performance-management processes [4], [13].

The final regression slope of Rp1.236 million per month and R^2 of 0.9198 show a strong linear association between time and revenue within the observed period. Nevertheless, a high R^2 based on six observations is not sufficient evidence of robust forecasting. The holdout MAPE of 6.31% is more credible than the in-sample MAPE of 3.14%, because the latter measures fit to data already used for estimation. Forecast-evaluation research emphasizes the need to distinguish explanatory fit from out-of-sample accuracy [10].

The prediction intervals also qualify the upward forecast. Although the point estimate reaches Rp24.34 million in September, the 95% prediction interval is approximately Rp20.73–27.94 million. This range reflects both residual variation and extrapolation beyond the observed months. The model does not include seasonality, holidays, weather, promotions, price changes, service mix, competitor actions, or operating-capacity constraints. These omitted factors may alter future revenue even when the historical trend appears linear.

The dashboard contribution lies in consolidating performance and forecast information into a decision-oriented view. Prior dashboard research emphasizes relevance, visual organization, and alignment with the user's role [5]–[7]. The revised dashboard follows these principles by limiting the main view to six KPI cards and four supporting visuals. In the SME context, a lightweight design may reduce complexity while still supporting structured decision-making, consistent with evidence that BI can improve SME competitiveness when the system is connected to actual managerial processes [2], [9].

This study has four principal limitations. First, it analyzes one business, so the results cannot be generalized to all laundry enterprises. Second, the six-month sample is too short to identify seasonality or structural changes. Third, the month index is the only regression predictor, so the model represents trend rather than operational causality. Fourth, dashboard usability was not evaluated with end users. Future research should use daily or weekly observations over at

Vol 10 No 2, July 2026, Page 185-190
ISSN 2548-8384 (online), ISSN 2548-8449 (print)
Available Online at https://ejurnal.stmik-budidarma.ac.id/index.php/ijics/index
DOI 10.30865/ijics.v10i2.9859

least 24 months, include service type, promotions, repeat-customer behavior, costs, weather, and capacity variables, compare linear regression with time-series and machine-learning baselines, and conduct user-acceptance testing. BI adoption risks and organizational readiness should also be evaluated before implementation in small firms [14].

4. CONCLUSION

The study demonstrates a consistent proof-of-concept workflow that combines KPI measurement, chronological validation of a linear revenue-trend model, and dashboard visualization for a laundry SME. During January–June 2024, total revenue reached Rp105,250,000, overall target achievement was 105.25%, and average revenue per transaction remained Rp50,000. Revenue performance was weakest in February and improved continuously from March to June. The chronological holdout produced MAE of Rp1,287,500, RMSE of Rp1,319,209, and MAPE of 6.31%. After refitting all six observations, the model $\hat{Y} = 13,216,666.67 + 1,235,714.29X$ generated point forecasts of Rp21.87 million, Rp23.10 million, and Rp24.34 million for July–September. The dashboard can help the owner monitor targets, operating volume, growth, and forecast ranges in one view. However, the small single-business dataset means that the results should be used for short-term exploratory planning, not as definitive evidence of future revenue. A production-ready system requires a longer observation period, richer predictors, comparative model testing, automated data integration, and user evaluation.

REFERENCES

[1] M. R. Llave, "Business Intelligence and Analytics in Small and Medium-sized Enterprises: A Systematic Literature Review," Procedia Computer Science, vol. 121, pp. 194–205, 2017, doi: 10.1016/j.procs.2017.11.027.

[2] A. Popovič, B. Puklavec, and T. Oliveira, "Justifying business intelligence systems adoption in SMEs: Impact of systems use on firm performance," Industrial Management & Data Systems, vol. 119, no. 1, pp. 210–228, 2019, doi: 10.1108/IMDS-02-2018-0085.

[3] V.-H. Trieu, "Getting value from Business Intelligence systems: A review and research agenda," Decision Support Systems, vol. 93, pp. 111–124, 2017, doi: 10.1016/j.dss.2016.09.019.

[4] M. D. Peters, B. Wieder, S. G. Sutton, and J. Wakefield, "Business intelligence systems use in performance measurement capabilities: Implications for enhanced competitive advantage," International Journal of Accounting Information Systems, vol. 21, pp. 1–17, 2016, doi: 10.1016/j.accinf.2016.03.001.

[5] O. M. Yigitbasioglu and O. Velcu, "A review of dashboards in performance management: Implications for design and research," International Journal of Accounting Information Systems, vol. 13, no. 1, pp. 41–59, 2012, doi: 10.1016/j.accinf.2011.08.002.

[6] A. Sarikaya, M. Correll, L. Bartram, M. Tory, and D. Fisher, "What Do We Talk About When We Talk About Dashboards?" IEEE Transactions on Visualization and Computer Graphics, vol. 25, no. 1, pp. 682–692, 2019, doi: 10.1109/TVCG.2018.2864903.

[7] J. Reinking, V. Arnold, and S. G. Sutton, "Synthesizing enterprise data through digital dashboards to strategically align performance: Why do operational managers use dashboards?" International Journal of Accounting Information Systems, vol. 37, Art. no. 100452, 2020, doi: 10.1016/j.accinf.2020.100452.

[8] R. Torres, A. Sidorova, and M. C. Jones, "Enabling firm performance through business intelligence and analytics: A dynamic capabilities perspective," Information & Management, vol. 55, no. 7, pp. 822–839, 2018, doi: 10.1016/j.im.2018.03.010.

[9] K. Ragazou, I. Passas, A. Garefalakis, and C. Zopounidis, "Business intelligence model empowering SMEs to make better decisions and enhance their competitive advantage," Discover Analytics, vol. 1, Art. no. 2, 2023, doi: 10.1007/s44257-022-00002-3.

[10] R. J. Hyndman and A. B. Koehler, "Another look at measures of forecast accuracy," International Journal of Forecasting, vol. 22, no. 4, pp. 679–688, 2006, doi: 10.1016/j.ijforecast.2006.03.001.

[11] A. de Myttenaere, B. Golden, B. Le Grand, and F. Rossi, "Mean Absolute Percentage Error for regression models," Neurocomputing, vol. 192, pp. 38–48, 2016, doi: 10.1016/j.neucom.2015.12.114.

[12] G. James, D. Witten, T. Hastie, and R. Tibshirani, An Introduction to Statistical Learning: with Applications in R, 2nd ed. Cham, Switzerland: Springer, 2021, doi: 10.1007/978-1-0716-1418-1.

[13] P. Rikhardsson and O. Yigitbasioglu, "Business intelligence & analytics in management accounting research: Status and future focus," International Journal of Accounting Information Systems, vol. 29, pp. 37–58, 2018, doi: 10.1016/j.accinf.2018.03.001.

[14] P. Poba-Nzaou, M. Galani, and C. Aloui, "Business Intelligence Adoption and Implementation Risk in SMEs: Insights From an Empirical Study in Tunisia," International Journal of Business Intelligence Research, vol. 13, no. 1, pp. 1–22, 2022, doi: 10.4018/IJBIR.305240.

[15] S. Kim and H. Kim, "A new metric of absolute percentage error for intermittent demand forecasts," International Journal of Forecasting, vol. 32, no. 3, pp. 669–679, 2016, doi: 10.1016/j.ijforecast.2015.12.003.