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Comparative Forecasting and Inventory Analytics for Web-Basedd Fabric Stock Control: A Case Study at BKR Textile Kudus

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Abstract
This study develops a web-based Smart Inventory system that integrates inventory recording, demand forecasting, inventory analytics, and replenishment recommendations for fabric stock control at BKR Textile Kudus. A Research and Development approach using the Prototype model was combined with quantitative comparative forecasting. The dataset comprised 400 fabric items and 12 months of stock-out history. Four one-month-ahead methods were tested: three-month Moving Average (MA), Weighted Moving Average (WMA) with 1:2:3 weights, Single Exponential Smoothing (SES) with alpha = 0.30, and rolling three-point Linear Regression (LR)-were evaluated through rolling-origin backtesting using MAD, MSE, and MAPE. Across 14,400 forecast-actual comparisons, MA produced the lowest average errors, with MAD of 5.167 rolls, MSE of 36.881, and MAPE of 5.166%. Inventory analysis identified three Critical items, 78 Low-stock items, 157 Normal items, and 162 Overstock items. The principal contribution is the integration of item-level comparative forecasting, safety stock, reorder points, inventory-status classification, and automated restock recommendations within one operational web platform. The system translates forecasting results into transparent decision information for a local textile company, although the findings remain specific to the one-year dataset and organizational setting examined.

Keywords:
Smart Inventory; Inventory Analytics; Fabric Stock Forecasting; Moving Average; Restock Recommendation.

1. INTRODUCTION

Inventory control in the textile industry is complicated by product variety, short product life cycles, and fluctuating customer demand. These conditions can create simultaneous risks of stockouts and excess stock when replenishment decisions rely only on current balances or managerial intuition. Demand forecasting provides an empirical basis for estimating near-term requirements from historical consumption patterns. This need is particularly relevant at BKR Textile Kudus, where fabric records must support purchasing decisions across hundreds of items with different demand rates and supplier lead times. (Kačmáry & Lörinc, 2023)

Predictive modelling converts historical observations into estimates of future outcomes. In time-series inventory forecasting, each method represents a different assumption about demand behaviour. Moving Average (MA) assigns equal importance to recent observations, Weighted Moving Average (WMA) places greater emphasis on the latest values, Single Exponential Smoothing (SES) updates forecasts recursively through a smoothing parameter, and Linear Regression (LR) estimates a linear demand trend. Previous studies demonstrate the practical use of MA, WMA, and SES for inventory forecasting, while LR provides an interpretable trend-based benchmark (Hadi et al., 2026; Huriati et al., 2022)

Predictive approaches range from transparent statistical models to machine-learning models that can incorporate nonlinear patterns and multiple external variables. Machine learning can improve stockout prediction when sufficiently long, varied, and well-labelled data are available (Liu et al., 2025; Royani et al., 2026). However, complex models are not automatically more appropriate for short item-level series. With only twelve observations per fabric item, the present study prioritizes methods whose calculations are explainable, computationally efficient, and straightforward to validate before operational implementation.

Existing studies commonly examine the performance of an individual forecasting method, including MA, WMA, or SES, but the resulting forecast is not always connected directly to inventory-control actions. Conversely, inventory information systems may record transactions without transparently comparing alternative forecasting models. This separation limits the ability of users to understand why a method is selected and how its forecast affects safety stock, reorder points, inventory status, and replenishment quantities. (Putra, 2023)

Accordingly, this study aims to develop a web-based Smart Inventory system for BKR Textile Kudus and determine which of four forecasting methods MA, WMA, SES, or LR-produces the lowest out-of-sample error for the available dataset. The novelty does not lie in proposing a new forecasting algorithm, but in integrating rolling origin method comparison at the individual item level with inventory classification and automated restock recommendations in a single operational workflow. This integration provides both empirical evidence about short-horizon fabric-demand forecasting and a practical, auditable decision-support mechanism for a local textile company.

2. RESEARCH METHOD

This study adopted a Research and Development approach using the Prototype model and quantitative comparative forecasting. It aimed to develop a web-based Smart Inventory system and compare Moving Average, Weighted Moving Average, Single Exponential Smoothing, and Linear Regression for forecasting fabric requirements at BKR Textile Kudus.

System development followed five iterative Prototype stages requirements communication, rapid planning, preliminary interface and process design, prototype construction, and evaluation followed by revision. Requirements were identified with the business owner and warehouse personnel and covered user roles, master data, stock transactions, forecasting, inventory analytics, and reporting (Syntetos et al., 2010). The researcher then performed scenario-based functional verification of authentication, data processing, forecast and error generation, inventory calculations, restocking recommendations, and report export. Analytical outputs were compared with Excel and Google Colab calculations; discrepancies were corrected and retested in the next iteration. This evaluation verified functional correctness rather than long-term user acceptance.

Validity and reliability were assessed at the data, forecasting, and system levels. Data validity was supported by triangulating company documentation with observations and informant confirmation, followed by completeness, duplicate, range, unit, and chronological checks. Forecast validity was examined through rolling-origin backtesting over nine out-of-sample months per item. Computational reliability was defined as reproducibility: identical cleaned inputs and fixed parameters were processed in Excel, Google Colab, and the Laravel application, while representative forecasts, error measures, reorder points, and restock outputs were compared using consistent rounding. Matching results across repeated calculations were treated as evidence of reliability. Construct-validity and Cronbach's alpha tests were not applied because the study used operational records rather than a psychometric questionnaire.

Table 1. Results of Data Quality, Forecast Validity, and Computional Reliability Assessment

Assesment	Procedure and criterion	Empirical result	Decision
Data completness	Check required identities and monthly demand records for missing values	400 items and 4,800 item month demand values , no missing required identity or monthly value	Valid
Uniqueness and range validity	Check duplicate fabric codes, numeric types, and negative monthly demand.	400 unique code, 0 duplicates, 0 nonnumeric values, and 0 negative monthly values	Valid
Forecast validity	Apply rolling origin backtesting from april to december for every item	Nine out of sample periods 3,600 forecast actual pairs per method, MA had the lowest MAPE (5.166%)	Valid
Computational reliability	Repeat fixed parameter calculations with identical cleaned inputs and consistent rounding across Excel, Goggle Colab, and Laravel	Representative forecasts, MAD, MSE, MAPE, reorder points, and restock outputs matched across repeated calculations	Reliable

The study population comprised all available fabric inventory records covering one consecutive twelve-month period from January to December. Because the source file contained month labels without a calendar year, no unsupported year was assigned. A census of 400 eligible fabric items produced 4,800 item-month observations. Data were obtained through observation, interviews, and company documentation and were checked for missing values, duplicates, invalid quantities, and unit inconsistencies.

A census approach was applied because all available fabric records satisfying the data requirements were analyzed. Therefore, no random sampling procedure was required. A record was included when it contained a valid fabric code, fabric name, fabric category, twelve chronologically ordered demand values, current stock information, supplier lead time, safety-stock value, and unit price. Records with missing identifiers, duplicated fabric codes, incomplete monthly series, nonnumeric demand values, or negative quantities were considered ineligible. Following the data-quality examination, 400 complete fabric series remained available for analysis.

The primary unit of analysis was an individual fabric item observed over twelve monthly periods. Demographic characteristics were not applicable because the forecasting model was developed from operational inventory records rather than a population of human respondents. The business owner and warehouse personnel only served as key informants during requirements identification and prototype evaluation; their responses were not subjected to demographic or inferential statistical analysis.

Data were collected through observation, semi-structured interviews, and documentation. Direct observation was conducted to understand how incoming stock, outgoing stock, stock balances, and restocking decisions were managed within the company. Particular attention was given to recording practices, information delays, recurring inventory problems, and the criteria used by warehouse personnel when deciding whether additional fabric should be ordered.

The collected records were organized according to fabric code and monthly period. Data preparation involved removing empty summary rows, checking duplicated fabric codes, standardizing column names, converting demand and stock fields into numeric values, and arranging monthly observations chronologically. All demand quantities were expressed in rolls to maintain measurement consistency.

Each fabric item was examined for missing and invalid values before forecasting. A record with an incomplete twelve-month demand sequence would have been excluded rather than statistically imputed because artificial replacement could change its temporal pattern. The final dataset contained 400 complete fabric items and did not require demand-value imputation.

The original records were retained separately from the processed dataset to preserve traceability. Preliminary calculations were performed and checked using Microsoft Excel and Google Colab. The forecasting and inventory control logic was subsequently implemented in the web application. Representative calculations were compared across the spreadsheet, Colab output, and application results to reduce the possibility of programming or formula errors.

Four forecasting methods were evaluated: Moving Average, Weighted Moving Average, Single Exponential Smoothing, and Linear Regression. The methods were applied separately to each fabric item so that differences in individual demand patterns could be considered.

The three period Moving Average generated the next forecast from the arithmetic mean of the three most recent actual observations:

a. Moving Average

$$F_t = \frac{A_{t-1} + A_{t-2} + A_{t-3}}{3}$$

b. Weighted Moving Average

$$F_t = \frac{1A_{t-3}+2A_{t-2}+3A_{t-1}}{6}$$

c. Single Exponnetial Smoothing

$$F_{t+1} = \alpha A_t + (1-\alpha)F_t$$

d. Linear Regression

$$\hat{Y} = a + bX$$

Forecasting performance was assessed through rolling-origin backtesting. The January–March observations provided the initial information needed to predict April. After the April actual value became available, it was added to the historical sequence before forecasting May. This procedure continued until December. Therefore, each fabric item produced nine forecast–actual pairs for each method, resulting in 3,600 evaluation pairs per method.

Three error measures were calculated: Mean Absolute Deviation, Mean Squared Error, and Mean Absolute Percentage Error. MAD measured the average absolute distance between actual and predicted demand:

a. Mean Absolute Deviation

$$MAD = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t|$$

b. Mean Squared Error

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2$$

c. Mean Absolute Percentage Error

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

Periods with an actual value of zero were excluded only from the MAPE denominator to prevent division by zero. Lower MAD, MSE, and MAPE values indicated better forecasting performance. MAPE was used as the principal ranking criterion because its percentage form enabled direct comparison among fabric items with different demand volumes. When two methods produced an equivalent MAPE, MAD and MSE were considered as supporting criteria. The method with the lowest aggregate MAPE was selected to produce the following month's demand forecast.

After selection of the best method, average daily demand was calculated as average monthly demand/30, the reorder point as ROP = (average daily demand × supplier lead time) + safety stock, and the following period's recommendation as Restock Quantity = max [0, next-period forecast + safety stock - current stock]. Critical denoted stock at the safety threshold; Low denoted stock approaching or crossing the reorder or minimum-stock boundary; Normal denoted stock within the operating range; and Overstock denoted stock above the configured maximum. Priority additionally considered supplier lead time, so recommended quantity and ordering urgency were reported as distinct outputs.

Data preparation, descriptive examination, and independent calculation checks were conducted using Microsoft Excel and Google Colab with Python-based data-processing libraries. The operational forecasting engine was implemented in PHP within the Laravel service layer, while MySQL stored fabric records, monthly demand, forecasting results, accuracy values, inventory analytics, and restocking recommendations. React and Recharts were used to present analytical results in tabular and graphical formats.

Descriptive analysis summarized demand, stock conditions, forecasting errors, and restocking requirements. Comparative analysis ranked the forecasting methods according to their average error measures. No hypothesis significance test was used to select the forecasting method because the research objective was to compare out-of-sample forecasting errors rather than examine causal relationships among variables.

The research was limited to one textile business and a twelve-month observation period. Although the dataset covered 400 fabric items, the relatively short temporal sequence restricted the model's ability to identify long-term trends, structural changes, and complex seasonal patterns. External factors such as promotional activity, supplier disruption, price changes, holidays, and market conditions were not incorporated into the forecasting models.

The SES smoothing parameter and WMA weights were applied consistently to all fabric items and were not optimized individually. A formal parameter-sensitivity analysis was not conducted because each item contained only twelve observations extensive item-level tuning over such a short series could overfit the evaluation period. Consequently, the fixed parameter choices may have influenced the relative performance of WMA and SES. Safety-stock values and the configured stock thresholds were obtained from the inventory-master data rather than estimated through a separate probabilistic service-level model. System verification focused on functional correctness and calculation consistency, not on long-term user acceptance or organizational impact.

These limitations were reduced by evaluating four forecasting methods instead of relying on one model, applying rolling-origin backtesting, using three complementary error measures, maintaining transparent calculation rules, and validating the application results against independent spreadsheet calculations. Nevertheless, the findings should be interpreted as evidence specific to the available BKR Textile dataset and research period.

3. RESULTS AND DISCUSSION

3.1. Forecasting Evaluation Results

The forecasting models were evaluated using monthly historical demand records for 400 fabric items covering the period from January to December. Demand data from January to March served as the initialization period for generating the forecasts, whereas model performance was assessed using observations from April to December. Therefore, each forecasting method generated nine pairs of forecasted and actual demand values for every fabric item. In total, the evaluation involved 3,600 forecast actual pairs for each method, producing 14,400 comparison pairs across all four forecasting methods.

The methods compared in this study comprised the three-month Moving Average (MA), Weighted Moving Average (WMA), Single Exponential Smoothing (SES), and Linear Regression (LR). Forecasting accuracy was assessed using Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). The most appropriate method was identified based on the smallest error values, as lower MAD, MSE, and MAPE results indicate that the predicted demand values are closer to the actual observations.

Table 2. Average forecasting accuracy of the four methods

Method	MAD	MSE	MAPE (%)	Descriptive Accuracy (%)	Rank
Moving Average	5.167	36.881	5.166	94.834	1
Weighted Moving Average	5.636	39.609	5.721	94.279	2
Single Exponential Smoothing	6.352	56.877	6.280	93.720	3
Linear Regression	9.392	113.088	9.943	90.057	4

Table 2 shows that the three-month Moving Average produced the lowest error values. Its average MAD was 5.167, indicating that the forecasts deviated from the actual monthly demand by approximately five rolls per observation. The MSE value of 36.881 was also the smallest, showing that this method produced fewer large forecasting errors. Furthermore, its MAPE of 5.166% was lower than those of the other methods.

The descriptive accuracy score was calculated. Therefore, the Moving Average achieved a score of 94.834%. This value is intended only as an accessible representation of the percentage error and should not be interpreted as a statistical probability or confidence level.

Compared with WMA, the selected MA method reduced MAD by approximately 8.32% and MSE by 6.89%. Its MAPE was also 0.556 percentage points lower. The difference indicates that assigning a greater weight to the latest observation did not improve the aggregate forecasting performance. The increased weight may have made WMA more responsive to short-term changes, but it also made the forecasts more sensitive to temporary demand fluctuations.

The difference was more noticeable when MA was compared with SES. The MA method generated an 18.66% lower MAD, a 35.16% lower MSE, and a 1.114-percentage-point lower MAPE. Although SES can gradually adapt to changes in demand, the smoothing parameter of (alpha=0.30) may have caused the forecasts to respond more slowly when monthly demand shifted.

Linear Regression produced the highest error values. Its MAPE reached 9.943%, while the MSE was 113.088. Compared with Linear Regression, MA reduced MAD by 44.99% and MSE by 67.39%. This result suggests that a single linear trend was not sufficient to represent the short-term demand pattern of the fabric products. Demand for textile materials may fluctuate because of customer orders, product types, seasonal preferences, and production requirements, rather than following a consistent upward or downward trend.

Overall, all four methods generated an average MAPE below 10%. Nevertheless, the three-month Moving Average was selected because it consistently produced the lowest aggregate MAD, MSE, and MAPE. The result supports evidence that a simple moving-average model can provide competitive short-horizon inventory forecasts (Huriati et al., 2022). It differs from studies in which WMA performed strongly (Puspitasari et al., 2023; Welda et al., 2024) reinforcing that model suitability depends on the demand pattern, forecast horizon, and parameter configuration of each dataset.

The superiority of MA should therefore be interpreted conditionally. Although 400 items provided broad cross-sectional coverage, each item contained only one annual cycle and nine out of sample periods, limiting the identification of seasonality and long-term change. Promotions, holidays, price changes, supplier disruption, and market conditions were not available as inputs, while WMA and SES parameters were not optimized per item. These constraints may affect the method ranking and limit generalisation beyond BKR Textile Kudus; the best-performing model should be re-evaluated as longer and more varied demand data become available.

3.1.1. Fabric Inventory Condition

Following the forecasting process, the inventory condition was assessed by comparing the current stock with the safety stock, reorder point, minimum stock, and maximum stock levels. The system classified each fabric item into Critical, Low, Normal, or Overstock status.

Table 3. Distribution of fabric inventory status

Inventory Status	Number of items	Percentage	Managerial Interpretation
Critical	3	0.75%	Immediate replenishment attention is required
Low	78	19.50%	Stock is approaching or below the required level
Normal	157	39.25%	Stock remains within the expected operating range
Overstock	162	40.50%	Purchasing should be controlled to prevent excess inventory
Total	400	100.00%	

These results demonstrate that a general purchasing policy cannot be applied uniformly to every fabric. Critical and Low items require faster action, whereas Overstock items require purchasing control or inventory reduction. The classification makes the inventory condition easier to interpret than relying solely on the total quantity stored in the warehouse.

3.1.2. Safety Stock and Reorder Point Results

Safety stock was used as a reserve to reduce the risk of shortages caused by demand variation and supplier delays. The reorder point was calculated by combining expected demand during the lead-time period with the assigned safety stock. An item should be considered for replenishment when its current stock approaches or falls below its reorder point.

Fabric code KN001 had an average monthly demand of 53 rolls, an average daily demand of approximately 1.77 rolls, a lead time of six days, and a safety stock of 27 rolls. Its reorder point was therefore approximately 37.6 rolls. Because its current stock was 69 rolls, the item remained above the reorder point and was classified as Normal.

In contrast, fabric code KN005 had an average monthly demand of 64 rolls, an average daily demand of approximately 2.13 rolls, a lead time of ten days, and a safety stock of 55 rolls. Its reorder point was approximately 76.3 rolls, while the current stock was only 70 rolls. The difference of approximately 6.3 rolls below the reorder point caused this fabric to be placed in the Low category.

Two products with similar current stock quantities may require different inventory decisions when their consumption rates and supplier lead times are different. Consequently, the reorder point provides a more informative purchasing signal than current stock alone.

3.1.3. Restock Recommendation Results

The restock recommendation was generated by combining the demand forecast, safety stock requirement, current stock, and supplier lead time. The calculation produced a total recommended quantity of 19,086 rolls for the planning period. Based on the recorded unit prices, the estimated procurement value was IDR 9,642,925,000. This figure represents a planning estimate and should not be interpreted as actual purchasing expenditure.

Table 4. Distribution of restock recommendation prorities

Priority	Number of items	Percentage	Recommended Action
Urgent	3	0.75%	Order immediately
High	11	2.75%	Prioritize in the nearest purchasing schedule
Normal/Planned	386	96.50%	Order according to the recommended date

The system identified three Urgent items and 11 High priority items. Thus, 14 fabric items, or 3.50% of the records, required prioritized procurement. The remaining 386 items were assigned to the Normal or Planned category. A Planned status does not mean that no replenishment is required. Instead, it indicates that the order can be placed according to the recommended schedule because sufficient time remains before the stock is expected to reach a risky level.

The distinction between inventory status and restock priority should also be considered. Inventory status represents the current stock position, whereas restock priority incorporates the expected requirement and the time available before replenishment is needed. Therefore, an item may have a relatively large recommended quantity but remain under Planned priority when its lead time and remaining stock still provide sufficient time to place an order (Swaminathan & Venkitasubramony, 2024).

Table 5. Ten largest recommended order quantities

Rank	Fabric Code	Fabric Name	Recommended Quantity	Priority
1.	KN021	Linen Soft	95 rolls	Planned
2	KN096	Voal Premium	95 rolls	Planned
3.	KN053	Baby Terry	94 rolls	Planned
4.	KN010	Katun Poplin	88 rolls	Urgent
5.	KN020	Rayon Batik Modern	88 rolls	Planned
6.	KN085	Knit Cardigan	88 rolls	Planned
7.	KN095	Batik Floral Kontemporer	88 rolls	Planned
8.	KN032	Satin Silk	87 rolls	Planned
9.	KN042	Japan Drill	87 rolls	Urgent
10.	KN052	Fleece CVC	87 rolls	Planned

Table 5 shows that a large recommended quantity does not automatically result in an urgent priority. Linen Soft and Voal Premium had the largest order recommendations, at 95 rolls each, but their orders could still be scheduled. Meanwhile, Katun Poplin and Japan Drill were marked as Urgent even though their recommended quantities were slightly lower. This difference occurs because priority is influenced not only by order quantity but also by the available stock position and the remaining time before replenishment is required.

The simultaneous appearance of stock shortages and overstock further demonstrates the importance of evaluating each item separately. Replenishment quantities should not be approved solely on the basis of forecasted demand. For items currently classified as Overstock, purchasing decisions should be reviewed together with the maximum stock limit and the planned consumption period. This control prevents the recommendation formula from creating unnecessary purchases.

3.2. System Implementation

The Smart Inventory system was developed using PHP 8.2 with the Laravel 12 framework for server-side processing and JavaScript with React 19 for the user interface. Inertia.js was used to integrate the backend and frontend components, while MySQL served as the primary database. Tailwind CSS supported the responsive interface design, and Recharts was used to visualize forecasting and inventory data on the dashboard.

3.2.1. Login Page

Presents the login page used to authenticate registered users before they can access the system. Users enter their email address and password, after which the system directs them to the appropriate interface according to their assigned role. Access is divided among administrators, warehouse staff, and owner-managers to prevent unauthorized use of inventory function.

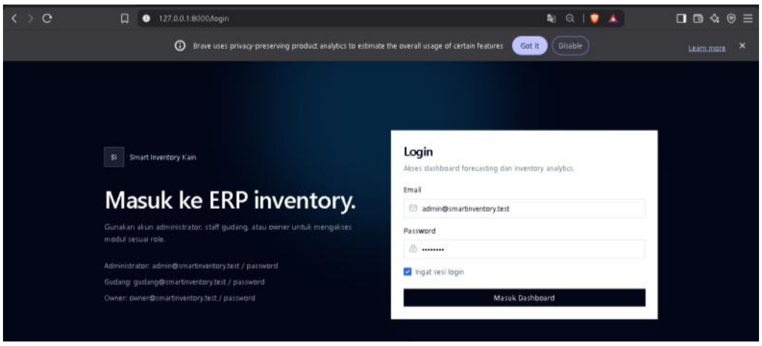

Figure 1. Login Page

3.2.2. Dashboard Page

The main dashboard, which provides a concise overview of the current inventory condition. It displays key information such as total fabric items, stock value, critical-stock alerts, recent transactions, and fabric movement. Graphical visualizations allow users to identify inventory conditions without examining each fabric record individuallythe main dashboard, which provides a concise overview of the current inventory condition. It displays key information such as total fabric items, stock value, critical-stock alerts, recent transactions, and fabric movement. Graphical visualizations allow users to identify inventory conditions without examining each fabric record individually.

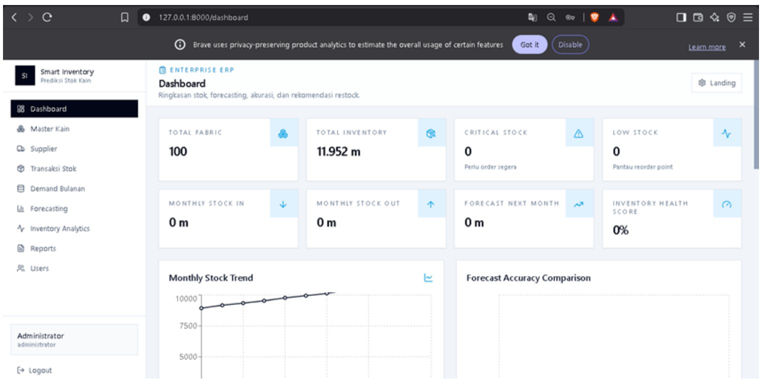

Figure 2. Dashboard Page

3.2.3. Master Data

Presents the interface for managing fabric data and recording stock transactions. Users can add or update fabric information, categories, suppliers, unit prices, lead times, and safety-stock values. The stock transaction feature records incoming stock, outgoing stock, and stock adjustments so that the available quantity remains consistent with warehouse activitie.

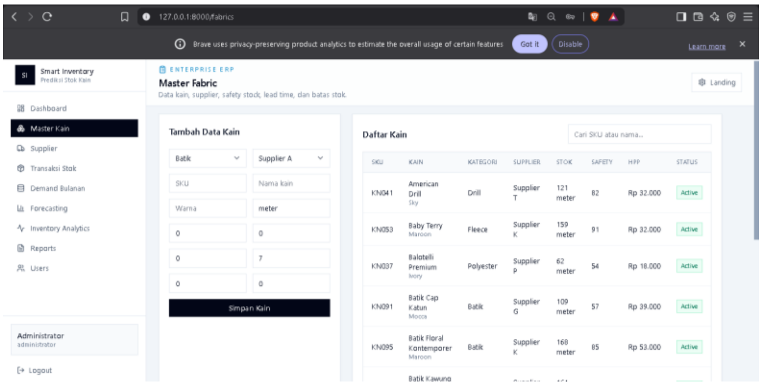

Figure 3. Master Data Page

3.2.4. Forecasting Page

The forecasting interface used to process historical monthly demand. The system applies Moving Average, Weighted Moving Average, Single Exponential Smoothing, and Linear Regression to the same dataset. It then calculates MAD, MSE, and MAPE and automatically ranks the methods according to their forecasting errors. For the evaluated dataset, Moving Average was placed first because it produced the lowest average MAPE.

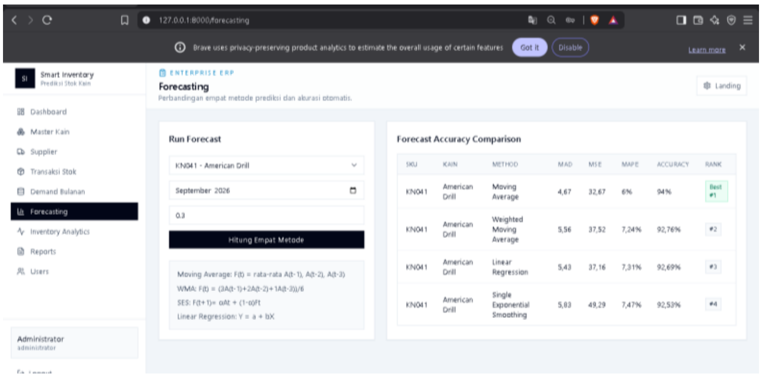

Figure 4. Forecasting Page

3.2.5. Inventory Analytics

Presents the inventory control results generated from demand, current stock, safety stock, and supplier lead time. The system calculates the average daily demand and reorder point for each fabric. It also classifies the current inventory into Critical, Low, Normal, or Overstock status, enabling users to recognize fabrics that require attention.

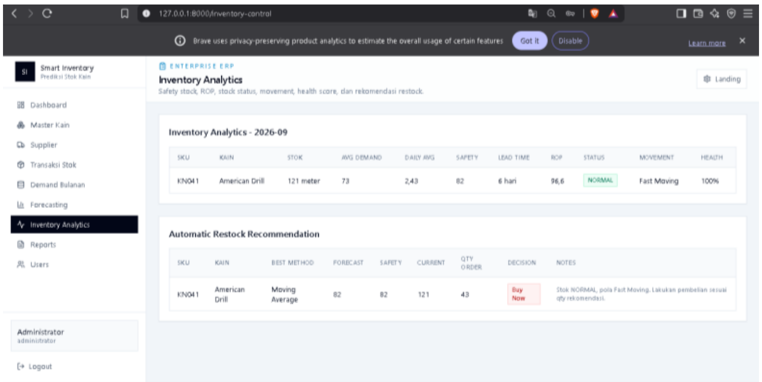

Figure 5. Inventory Analytics

3.2.6. Reports Page

The reporting interface, where users can review and export forecasting and inventory results. Reports can be downloaded in Excel or PDF format to support documentation, managerial evaluation, and purchasing decisions. Through these integrated interfaces, the system converts historical demand and stock data into information that can be directly used in inventory operations.

Smart Inventory dan Prediksi Stok Kain

Tipe laporan: monthly | Periode: 2026-09

Forecast Terbaik

SKU	Kain	Metode	MAD	MSE	MAPE	Akurasi
KN041	American Drill	moving_average	4.6667	32.6667	6.0001	94.00%

Inventory Analytics

SKU	Kain	Stok	ROP	Status	Movement	Health
KN041	American Drill	121.00 meter	96.60	NORMAL	Fast Moving	100.00

Rekomendasi Restock

SKU	Kain	Forecast	Safety	Qty Order	Keputusan	Catatan
KN041	American Drill	82.00	82.00	43.00	Buy Now	Stok NORMAL, pola Fast Moving. Lakukan pembelian sesuai qty rekomendasi.

Figure 6. Reports Page

3.2.7. Landing Page

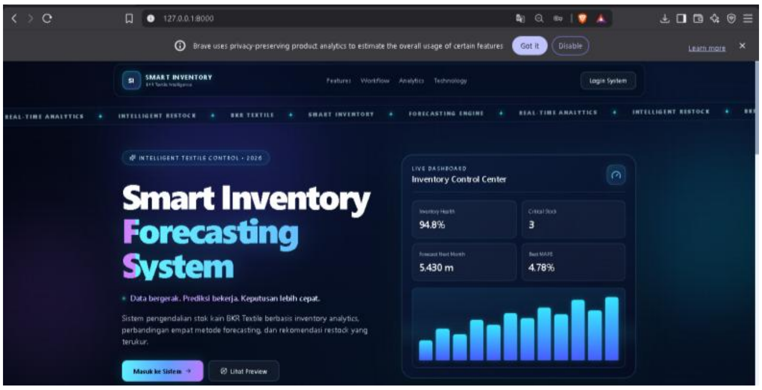

Figure 7. Landing Page

4. CONCLUSION

This study developed a web-based Smart Inventory system to support fabric stock management at BKR Textile Kudus. Based on 12 months of demand data from 400 fabric items, the three-month Moving Average achieved the best forecasting performance, with MAD of 5.167, MSE of 36.881, and MAPE of 5.166%. The inventory analysis identified three Critical items, 78 Low-stock items, 157 Normal items, and 162 Overstock items, indicating that the company faces both shortage and excess-inventory risks.

The developed system integrates demand forecasting, stock monitoring, safety stock, reorder points, and restock recommendations into a single dashboard. This integration can assist warehouse staff and managers in making more consistent, timely, and data-driven purchasing decisions. Further research should apply a longer observation period and evaluate the system's actual impact on stockouts, excess inventory, purchasing costs, and order fulfilment after full operational implementation (Liu et al., 2025).

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