engineering proceedings

Proceeding Paper

Integrating Trend Moment Forecasting Method into a Web-Based E-Commerce System for Skincare Business †

Amar Ma'ruf, Ika Safitri Windiarti *, Sutami and Setio Ardy Nuswantoro

Computer Science, Faculty of Business and Informatics, Universitas Muhammadiyah Palangkaraya (UMPR), Jl. RTA Milono Km. 1,5, Kel Langkai, Kota Palangkaraya 73111, Indonesia; amarmrf016@gmail.com (A.M.); tmy.tamy2@gmail.com (S.); setioardy@gmail.com (S.A.N.)

* Correspondence: ika.windiarti@umpr.ac.id

† Presented at the 9th Mechanical Engineering, Science and Technology International Conference (MEST 2025), Samarinda, Indonesia, 11–12 December 2025.

Abstract

The skincare business in Southeast Asia is rapidly expanding, requiring SMEs to adopt digital tools that support more accurate and data-driven decision-making. This study presents the integration of the Trend Moment forecasting method into a web-based e-commerce system developed for a skincare SME, Ainah Beautycare. Using 24 months of historical sales data, the system automatically generates short-term demand forecasts to assist inventory planning, stock replenishment, and production scheduling. The model achieved a forecasting accuracy of 9.54% MAPE, demonstrating that simple statistical methods can provide reliable operational insights when embedded directly into digital platforms. By linking transactional data with predictive analytics, the system enables business owners to transition from intuition-based decision-making to structured, data-informed workflows. The proposed solution illustrates a practical, lightweight approach to initiating digital transformation for skincare SMEs, offering scalability toward more advanced analytical capabilities in future developments.

Keywords: e-commerce; digital transformation; Industry 4.0; sales forecasting; time series; trend moment

1. Introduction

The Fourth Industrial Revolution (Industry 4.0) calls for increasing levels of automation, digital intelligence, and data-driven operations in enterprises of all sizes. For SMEs in Southeast Asia, particularly in the booming skincare sector, competition is no longer shaped solely by product quality, but also by digital capabilities, responsiveness, and operational agility [1–5]. Despite their economic significance, many Indonesian SMEs struggle with digital readiness due to limited technological literacy, low IT resources, and fragmented business processes [6–9].

Digital transformation (DT) frameworks emphasize the importance of data analytics as a foundational capability for SMEs transitioning into Industry 4.0 [10–12]. However, many SMEs lack the infrastructure or skills to adopt advanced analytics such as machine learning, ARIMA, or deep learning [13–15]. As a result, practical and lightweight forecasting models—such as the Trend Moment method—offer an accessible alternative that still enables data-driven decision-making [16–18].

This study develops a web-based e-commerce system integrated with a Trend Moment demand forecasting module for Ainah Beautycare, an emerging skincare SME in Indonesia.

Academic Editors: Rusandi Noor, Sigiet Haryo Pranoto, Arbansyah, Sarjito, Waluyo Adi Siswanto, Agus Dwi Anggono and Taghfirul Azhima Yoga Siswa

Published: 18 June 2026

Using 24 months of historical sales data, the system generates short-term forecasts to support inventory management and stock planning. The study contributes to the digital transformation discourse by demonstrating how simple analytics embedded in digital platforms can enhance SME competitiveness and accelerate Industry 4.0 adoption [19–22].

2. Related Work

2.1. Digital Transformation Approaches for SMEs

Prior research highlights that digital transformation (DT) is increasingly essential for SMEs to enhance efficiency, competitiveness, and long-term sustainability in the industry 4.0 era [1–5]. SMEs adopting digital tools such as e-commerce platforms, cloud-based applications, and basic analytics demonstrate improved agility, customer reach, and operational performance [6–8]. However, persistent constraints—including limited financial resources, inadequate digital skills, and fragmented IT infrastructures—continue to inhibit DT adoption in many developing regions [9–11]. These findings collectively emphasize that SMEs require contextualized strategies that enable gradual, low-cost digital adoption.

2.2. Industry 4.0 Enablement and Readiness Models

Industry 4.0 frameworks underscore the integration of automation, cyber-physical systems, data analytics, and intelligent decision-support technologies [12–15]. For SMEs, achieving full-scale Industry 4.0 readiness remains challenging due to the complexity and cost of advanced technologies. Consequently, studies recommend phased adoption strategies where SMEs begin with accessible tools—such as web platforms, digitized workflows, and simple analytics—before transitioning to more sophisticated capabilities like IoT integration and predictive automation [16–18]. Research further shows that incremental capability development enhances SME resilience and competitiveness while reducing technological risk [19–23].

2.3. Forecasting Technologies in SME Operations

Forecasting plays a central role in optimizing inventory management, procurement planning, and production scheduling. Although machine learning and hybrid models can deliver superior accuracy, they often demand computational resources and expertise that SMEs may not possess [24,25]. Consequently, lightweight statistical models—such as moving averages, exponential smoothing, and Trend Moment analysis—are preferred alternatives due to their simplicity, interpretability, and minimal computational requirements [26–29]. These models are particularly suitable when SMEs have limited historical data, as is common in micro-scale retail and skincare businesses.

2.4. Integrated E-Commerce and Forecasting Systems

While the literature provides extensive discussions on forecasting methods and e-commerce adoption independently, fewer studies examine integrated systems that combine online sales platforms with embedded forecasting capabilities. Existing works highlight that embedding analytics into operational systems can enhance decision-making, but implementations for SMEs remain limited due to resource constraints [17,18,30]. This creates an opportunity for practical, system-level solutions that support SMEs' transition toward data-driven operations without requiring advanced infrastructures.

2.5. Research Gap

Across the reviewed studies, two key gaps emerge:

1. Limited implementation of forecasting models directly within SME e-commerce platforms, and

2. Lack of lightweight, accessible digital solutions tailored for micro-scale product-based businesses.

This study addresses both gaps by integrating the Trend Moment forecasting method into a web-based e-commerce system designed for Ainah Beautycare. The proposed solution demonstrates how simple statistical forecasting embedded within daily operations can support early-stage digital transformation and Industry 4.0 readiness for SMEs.

3. Methodology

3.1. Data Collection

Data was collected from Ainah Beautycare, an SME skincare retailer based in Palangkaraya, Indonesia. Sales records for monthly total units sold across all skincare product lines were obtained from August 2022 through July 2024. After cleaning for missing or anomalous entries, the dataset consisted of 24 observations as shown in Table 1.

Table 1. Sales records for monthly total units sold from August 2022–July 2024.

Month	Year	Sales (Yi)	Time (Xi)	XiYi	Xi2
August	2022	109	1	109	1
September	2022	120	2	240	4
October	2022	85	3	255	9
November	2022	83	4	332	16
December	2022	87	5	435	25
January	2023	102	6	612	36
February	2023	97	7	679	49
March	2023	96	8	768	64
April	2023	89	9	801	81
May	2023	115	10	1150	100
June	2023	101	11	1111	121
July	2023	91	12	1092	144
August	2023	89	13	1157	169
September	2023	96	14	1344	196
October	2023	114	15	1710	225
November	2023	104	16	1664	256
December	2023	101	17	1717	289
January	2024	113	18	2034	324
February	2024	88	19	1672	361
March	2024	120	20	2400	400
April	2024	94	21	1974	441
May	2024	80	22	1760	484
June	2024	96	23	2208	529
July	2024	96	24	2304	576

3.2. Trend Moment Forecasting Model

The Trend Moment method assumes a linear relationship over time:

$$Y_t = a + bX_t + \varepsilon_t$$

where

Y_t = observed sales in period t.

X_t = time index $(1, 2, 3, \ldots, n)$.

a = intercept (estimated as mean of Y minus b times mean of X).

b = slope, computed by:

$$b = \frac{\sum_{t=1}^{n} \left(X_t - \overline{X}\right)\left(Y_t - \overline{Y}\right)}{\sum_{t=1}^{n} \left(X_t - \overline{X}\right)^2}$$

$$a = \overline{Y} - b\overline{X}$$

Forecasts for future periods (e.g., months (n + 1, n + 2, . . .)) are generated by substituting (X) values accordingly.

3.3. System Development

The system is a web-based application supporting:

- Customer module: product browsing, ordering.
- Admin module: inventory, product management, sales records, and prediction module.
- Prediction module: taking historical sales data, applying Trend Moment method, outputting forecasts and visual reports.

Technologies used: PHP 8.0 (backend), MySQL 8.0 (database), deployed on XAMPP 8.2 for development. System design uses UML artifacts: Use Case Diagram, Class Diagram, Sequence Diagrams, Activity Diagrams, ERD.

3.4. Evaluation Metrics

Forecast accuracy is evaluated using:

Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=0}^{n} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right|$$

where Y_t is the forecast value for period t.

Additionally, system functionality is tested via Black-Box testing to ensure that all modules (ordering, prediction, reporting) behave correctly as per functional requirements.

4. System Design and Implementation

4.1. Architecture

The system architecture uses a three-tier design to ensure clarity and scalability. The Presentation Layer provides the web interface for customers and administrators. The Application Layer manages core business processes, including order handling, forecasting calculations, and sales reporting. The Data Layer stores essential information in a MySQL database, such as product data, user accounts, and historical sales records. This structure streamlines system operations and supports smooth integration between the e-commerce platform and the forecasting module.

4.2. UML Modeling

The system's behavior is illustrated through several UML diagrams. The Use Case Diagram defines two main actors—Admin and Customer—where the admin manages products, views sales, and runs the forecasting feature, while the Customer browses items, places orders, and checks order history. The Activity Diagram outlines the forecasting workflow, including selecting the period, processing historical sales data, running the Trend Moment calculation, and displaying the results. The Sequence Diagram shows how the interface, application logic, and database interact when a prediction request is executed. These diagrams collectively clarify system processes and user interactions.

4.3. Prediction Module Interface

The forecasting module enables the admin to define the start and end periods of historical data, set the desired forecast horizon, and generate predictions for upcoming months. The system outputs forecasted sales values, error metrics, and a graphical visualization that includes both historical data and projected trend lines. Interface screenshots and generated graphs further illustrate the forecasting results within the platform.

Figure 1 shows the main page of the web-based e-commerce system developed for the skincare business. The interface presents product categories, promotional banners, and featured items to facilitate user navigation and improve the overall customer experience. The design emphasizes simplicity and responsiveness, enabling customers to browse skincare products efficiently across different devices. This landing page serves as the central access point for customers and integrates seamlessly with the platform's shopping cart, checkout process, and user account management modules.

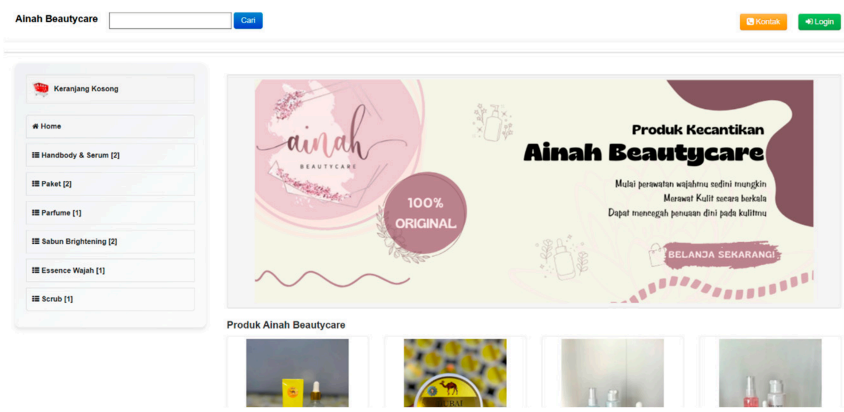

Figure 1. Main Page of the Web-Based E-Commerce System.

Figure 2 displays the sales report page, which provides administrators with real-time information on transaction data and historical sales trends. The page includes a tabulated summary of daily, weekly, and monthly sales, enabling the business owner to monitor performance and identify demand patterns. This reporting module acts as the primary data source for forecasting, as it automatically compiles sales records generated from the e-commerce system. By digitizing sales monitoring, the system reduces manual reporting errors and supports more informed decision-making.

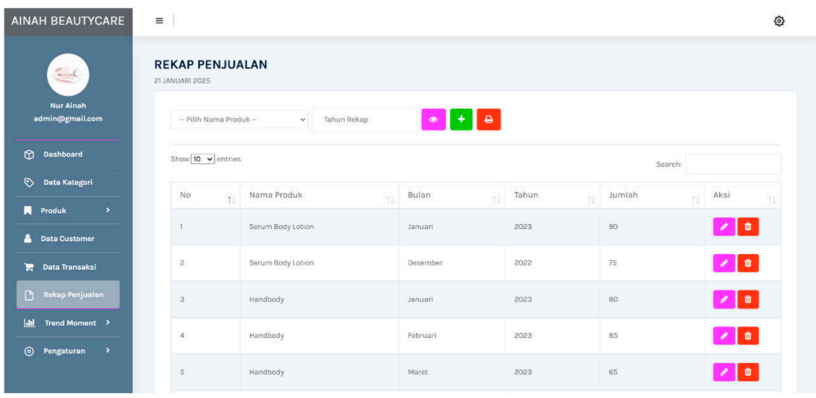

Figure 2. Sales Report Page.

Figure 3 illustrates the sales forecasting page, where the Trend Moment forecasting method is executed using historical sales data. This page allows administrators to view input parameters, initiate forecasting processes, and access predictive outputs. The interface displays the fitted trend line, the computed forecasting parameters (intercept and slope), and visualizations of predicted values. This module bridges operational data with analytical capabilities, making forecasting accessible to users without technical expertise.

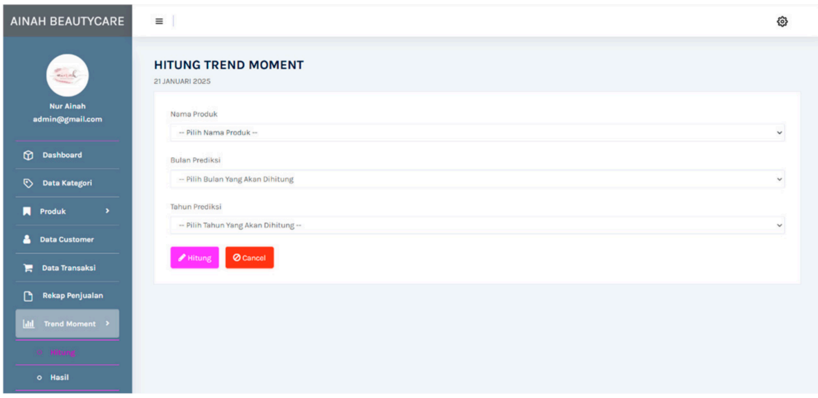

Figure 3. Sales Forecasting Page.

Figure 4 presents the forecasting results page, which summarizes the predicted sales values for upcoming months. The results are shown in both numerical and graphical formats, enabling users to quickly interpret expected demand. This page includes key indicators such as forecasted quantities, error metrics, and visual trend projections. By providing clear and actionable forecasting insights, the system helps skincare SMEs optimize inventory levels, streamline production planning, and enhance business responsiveness.

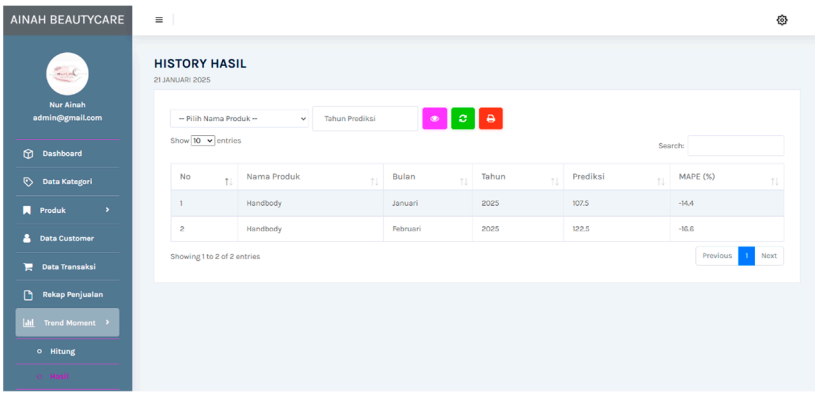

Figure 4. Forecasting Results Page.

5. Results and Discussion

5.1. Model Fit and Accuracy

The Trend Moment model successfully captures the mild downward trend in sales (slope $b < 0$). The in-sample forecasting error is relatively low:

- Overall MAPE = 9.54%
- Within threshold for operational-level forecasting
- Residuals are approximately symmetric $\rightarrow$ no major bias

Table 2 summarizes the key statistical parameters computed from the 24-month sales dataset, including the sums of X, Y, XY, and X^2. These values form the basis for estimating the Trend Moment model's slope and intercept, which are essential for generating fitted and forecasted sales values.

Table 2. Dataset Parameter Calculation for August 2022–July 2024.

Σ (Yi)	Σ (Xi)	ΣXiYi	ΣXi2
2408	300	30,174	4900

Table 3 presents the performance metrics of the Trend Moment model. The results include the computed intercept and slope, error statistics, and the overall MAPE of 9.54%. These indicators confirm that the model provides sufficiently accurate predictions for short-term operational use.

Table 3. Model Performance Summary for August 2022–July 2024.

Intercept (a)	Slope (b)	Overall MAPE (%)	Residual Range
99.0905	−0.0409	9.54	−14.8 to +15.3

5.2. Forecast Results (12 Months Ahead)

Table 4 presents the forecasted sales values generated by the Trend Moment method for the months following July 2024. The results show a stable and gradually declining linear trajectory, consistent with the negative slope of the fitted model. Although the changes between months are minimal, this pattern reflects the steady demand typically observed in skincare products, where customer purchasing behavior is relatively consistent over time. The model's ability to provide smooth and predictable forecasts demonstrates its suitability for short-term planning, particularly in small-scale businesses with limited data availability.

Table 4. Forecast Values generated by Trend Moment Method.

Month	Year	Time (X)	Forecast (Y)
August	2024	25	98.08
September	2024	26	98.04
October	2024	27	98.00
November	2024	28	97.96
December	2024	29	97.92
January	2025	30	97.88
February	2025	31	97.84
March	2025	32	97.80
April	2025	33	97.76
May	2025	34	97.72
June	2025	35	97.68
July	2025	36	97.64

The forecast values offer practical guidance for inventory control, production scheduling, and procurement planning. For skincare SMEs, anticipating monthly demand is essential due to product shelf life considerations and fluctuating customer interest driven by trends and promotional activities. By providing clear numerical predictions, Table 4 helps business owners avoid overstocking or stockouts, supporting more efficient resource allocation. Furthermore, the forecasting output serves as a foundational analytical layer that can be expanded into more advanced models as the business progresses in its digital transformation journey.

Table 5 presents the short-term forecast evaluation for August to December 2024, comparing actual sales with Trend Moment predictions and calculating the monthly MAPE. The results show that the model performs reliably, with low errors in August (2.2%), October (0.3%), and December (8.4%), indicating strong alignment with typical demand levels. Higher deviations in September (12.7%) and November (8.5%) suggest temporary fluctuations likely influenced by promotional activity or seasonal shifts common in skincare markets. The Trend Moment method provides sufficiently accurate short-term forecasts to support inventory planning and production decisions for skincare SMEs.

Table 5. Short-term Forecast results and Monthly MAPE.

Month	Actual Sales	Forecast (Trend Moment)	MAPE per Month (%)	Time Index (X)
Aug 2024	100	97.8	2.2	25
Sep 2024	112	97.7	12.7	26
Oct 2024	98	97.7	0.3	27
Nov 2024	90	97.7	8.5	28
Dec 2024	90	97.6	8.4	29

Table 6 provides a detailed view of the in-sample performance of the Trend Moment model across 24 months of historical sales data, comparing actual values with fitted estimates and reporting the corresponding errors. The results show that the fitted values generally follow the direction of the actual sales trend, despite natural fluctuations in the skincare market caused by promotions, seasonal variations, and customer behavior shifts.

Table 6. In-sample performance of Trend Moment model (overall MAPE = 9.54%).

Month	Year	Xi	Actual (Yi)	Fitted (Y_hat)	Error	AbsPct Error (%)
August	2022	1	109	99.05	9.95	9.13
September	2022	2	120	99.01	20.99	17.49
October	2022	3	85	98.97	−13.97	16.44
November	2022	4	83	98.93	−15.93	19.19
December	2022	5	87	98.89	−11.89	13.67
January	2023	6	102	98.85	3.15	3.09
February	2023	7	97	98.81	−1.81	1.86
March	2023	8	96	98.77	−2.77	2.88
April	2023	9	89	98.73	−9.73	10.93
May	2023	10	115	98.69	16.31	14.19
June	2023	11	101	98.64	2.36	2.33
July	2023	12	91	98.60	−7.60	8.36
August	2023	13	89	98.56	−9.56	10.74
September	2023	14	96	98.52	−2.52	2.63
October	2023	15	114	98.48	15.52	13.61
November	2023	16	104	98.44	5.56	5.35
December	2023	17	101	98.40	2.60	2.57
January	2024	18	113	98.36	14.64	12.96
February	2024	19	88	98.32	−10.32	11.72
March	2024	20	120	98.28	21.72	18.10
April	2024	21	94	98.24	−4.24	4.51
May	2024	22	80	98.20	−18.20	22.74
June	2024	23	96	98.15	−2.15	2.24
July	2024	24	96	98.11	−2.11	2.20

Months with higher Absolute Percentage Error—such as September 2022 (17.49%), November 2022 (19.19%), March 2024 (18.10%), and May 2024 (22.74%)—indicate irregular demand spikes that a linear model is not designed to fully capture. Nevertheless, many months exhibit low errors below 5%, demonstrating that the Trend Moment approach effectively models the overall trend. With an overall MAPE of 9.54%, the table confirms that the model provides sufficiently accurate and stable estimations for operational forecasting and decision support within the skincare business context.

5.3. Figures

Figure 5 illustrates the comparison between actual sales values, fitted values generated by the Trend Moment model, and the 12-month ahead forecast.

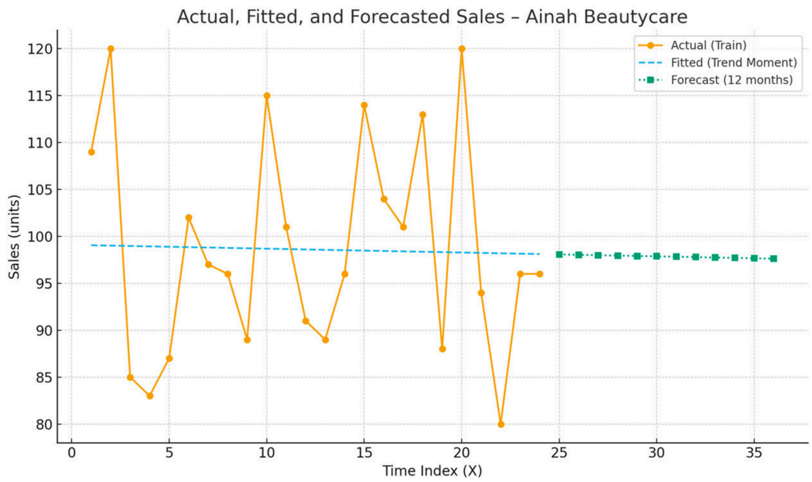

Figure 5. Actual vs. Fitted vs. Forecast (Trend Moment).

The plot demonstrates that the fitted values closely follow the overall pattern of the historical data across the 24-month period, indicating that the Trend Moment model is capable of capturing the general direction and magnitude of sales fluctuations. Although minor deviations occur in months with unusually high or low demand, the fitted line successfully represents the long-term linear trend of the series. The model reveals a mild downward slope, consistent with the negative coefficient $b = -0.0409$, suggesting a gradual decline in monthly sales over the observation period.

Overall, Figure 5 confirms that the Trend Moment method provides an interpretable and sufficiently accurate representation of short-term sales dynamics, making it suitable for resource-constrained SMEs pursuing early-stage digital transformation.

Figure 6 presents the monthly Absolute Percentage Error (APE) values across the 24-month training dataset. Collectively, Figure 6 demonstrates that the Trend Moment model provides predictable and stable error behavior, making it a practical choice for integration into SME e-commerce platforms as a lightweight forecasting tool.

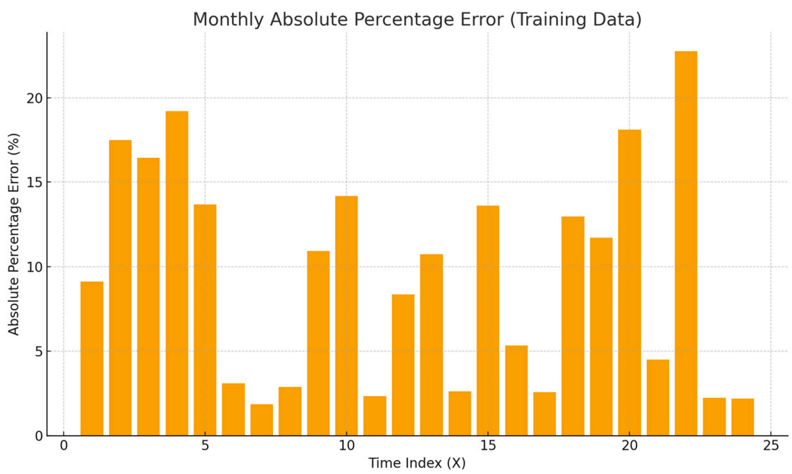

Figure 6. Monthly absolute percentage error (training data).

5.4. Discussion

The integration of the Trend Moment forecasting method into a web-based e-commerce system offers a practical and effective approach for enhancing operational decision-making in the skincare business domain. The results indicate that the forecasting module successfully generates short-term demand estimations that align closely with historical sales patterns, achieving a MAPE of 9.54%. This level of accuracy is particularly valuable for skincare SMEs, where demand is often influenced by marketing cycles, product trends, and seasonal variations.

Embedding the forecasting engine directly into the e-commerce platform creates a seamless data flow from transaction records to predictive analytics. This integration not only automates the forecasting process but also increases the usability of the system for business owners who may not possess formal analytical expertise. Through this architecture, the system functions as an intelligent decision-support tool capable of informing stock management, production planning, and procurement activities.

From a broader perspective, the study demonstrates how simple statistical forecasting can strengthen the digital ecosystem of a skincare business. By transforming routine sales data into actionable insights, the system supports the transition from intuition-driven operations to structured, data-driven workflows. This shift contributes meaningfully to early-stage digital transformation, enabling skincare SMEs to adopt analytical capabilities without requiring advanced infrastructure or specialized human resources.

Furthermore, the integration approach highlights scalability potential. The Trend Moment model serves as an initial analytical layer that can be expanded to more advanced forecasting techniques as the business grows. This modular design ensures that the e-commerce platform can evolve into a more comprehensive digital system aligned with higher levels of Industry 4.0 maturity.

6. Conclusions

This study concludes that integrating the Trend Moment forecasting method into a web-based e-commerce system offers a practical, accessible, and impactful solution for skincare businesses seeking to enhance operational efficiency. The forecasting module demonstrated reliable performance, achieving a MAPE of 9.54%, which is sufficiently accurate for short-term decision-making related to inventory control, production scheduling, and supply planning. The seamless incorporation of forecasting into the digital sales environment ensures that insights are generated automatically and can be directly utilized by business owners without requiring analytical expertise.

The research further emphasizes that even simple forecasting methods can catalyze digital transformation within SMEs by enabling data-driven decision-making and reducing dependence on manual estimation. For skincare businesses operating in highly dynamic and trend-driven markets, this capability contributes to improved responsiveness, reduced stock-related risks, and greater competitive advantage.

Future developments may explore the incorporation of advanced forecasting models such as ARIMA, Prophet, or LSTM to account for nonlinear patterns and seasonality in skincare demand. Additional enhancements could include extending the system into multi-product environments, integrating supplier and logistics data, and adopting IoT-based monitoring for real-time inventory tracking. These extensions will further strengthen the role of forecasting as a core intelligence component in web-based e-commerce ecosystems for SMEs.

Author Contributions: Conceptualization, A.M.; Methodology, I.S.W., S.A.N.; System Design and Coding, A.M., S.; Data Curation and Sales Forecasting Analysis, S.A.N., S.; AI Narration and Concept Development, I.S.W., A.M.; Writing—Original Draft Preparation, S.A.N., A.M.; Writing—Review and Editing, S., I.S.W.; Supervision, I.S.W.; Project Administration, A.M.; Corresponding Author, I.S.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Purnomo, S.; Nurmalitasari, N.; Nurchim, N. Digital transformation of MSMEs in Indonesia: A systematic literature review. *J. Manag. Digit. Bus.* **2024**, *4*, 301–312. [CrossRef]
2. Kallmuenzer, A.; Mikhaylov, A.; Chelaru, M.; Czakon, W. Adoption and performance outcome of digitalization in small and medium-sized enterprises. *Rev. Manag. Sci.* **2025**, *19*, 2011–2038. [CrossRef]
3. Nazaruddin, I.; Utami, E.R.; Rahmawati, E. Digitalization challenges for SMEs: A systematic literature review perspective and future research. *JBTI J. Bisnis Teor. Dan Implementasi* **2024**, *15*, 15–43. [CrossRef]
4. da Silva, N.A.; Abreu, J.L.; Orsolin Klingenberg, C.; Antunes Junior, J.A.V.; Lacerda, D.P. Industry 4.0 and micro and small enterprises: Systematic literature review and analysis. *Prod. Manuf. Res.* **2022**, *10*, 696–726. [CrossRef]
5. Huang, K.; Wang, K.; Lee, P.K.; Yeung, A.C. The impact of industry 4.0 on supply chain capability and supply chain resilience: A dynamic resource-based view. *Int. J. Prod. Econ.* **2023**, *262*, 108913. [CrossRef]
6. Satar, M.S.; Alharthi, S.; Alarifi, G.; Omeish, F. Does digital capabilities foster social innovation performance in social enterprises? Mediation by firm-level entrepreneurial orientation. *Sustainability* **2024**, *16*, 2464. [CrossRef]
7. Choon, W.C.; Ali, S.M. Digital transformation and sustainable supply chain performance: A systematic literature review. *J. Technol. Manag. Technopreneurship (JTMT)* **2025**, *13*. [CrossRef]
8. Anatan, L.; Nur. Micro, small, and medium enterprises' readiness for digital transformation in Indonesia. *Economies* **2023**, *11*, 156. [CrossRef]
9. Ben Slimane, S.; Coeurderoy, R.; Mhenni, H. Digital transformation of small and medium enterprises: A systematic literature review and an integrative framework. *Int. Stud. Manag. Organ.* **2022**, *52*, 96–120. [CrossRef]
10. Huang, W.; Ichikohji, T. A review and analysis of the business model innovation literature. *Heliyon* **2023**, *9*, e17895. [CrossRef] [PubMed]
11. Low, M.P.; Seah, C.S.; Cham, T.H.; Teoh, S.H. Digitalization adoption for digital economy: An examination of Malaysian small medium-sized enterprises through the technology–organization–environment framework. *Bus. Process Manag. J.* **2022**, *28*, 1473–1494. [CrossRef]
12. Gold, K.L. Effects of industry 4.0 on small and Medium-Scale enterprises: An analytical and bibliometric review. *Sage Open* **2025**, *15*, 1–18. [CrossRef]
13. Valdez-Juárez, L.E.; Ramos-Escobar, E.A.; Hernández-Ponce, O.E.; Ruiz-Zamora, J.A. Digital transformation and innovation, dynamic capabilities to strengthen the financial performance of Mexican SMEs: A sustainable approach. *Cogent Bus. Manag.* **2024**, *11*, 2318635. [CrossRef]
14. Kulkarni, V.N.; Gaitonde, V.N.; Kotturshettar, B.B. Product lifecycle management (PLM): A key enabler in implementation of industry 4.0: A key enabler in implementation of industry 4.0. In *Handbook of Smart Materials, Technologies, and Devices: Applications of Industry 4.0*; Springer International Publishing: Cham, Switzerland, 2022; pp. 349–380. [CrossRef]
15. Nozari, H.; Sadeghi, M.E.; Najafi, S.E. Quantitative Analysis of Implementation Challenges of IoT-Based Digital Supply Chain (Supply Chain 0/4). *arXiv* **2022**, arXiv:2206.12277. [CrossRef]
16. Ma, L.; Zhang, X.; Dong, L. Enhancing sustainable performance: The innovative strategy of digital transformation leading green collaborative management. *Sustainability* **2023**, *15*, 13085. [CrossRef]
17. Windiarti, I.S.; Putri, C.; Haryadi, H.; Prabowo, A. Pemberdayaan masyarakat melalui e-commerce pemesanan buket bunga responsif di Bouqet_PKY. *Abdimas Papua J. Community Serv.* **2024**, *6*, 65–71. [CrossRef]
18. Prabowo, A.; Hidayat, D.; Windiarti, I.S. Penguatan UMKM Kesenian melalui Digitalisasi Penyewaan Baju Adat Berbasis CodeIgniter di Sanggar Riak Renteng Tingang. *Abdimas Papua J. Community Serv.* **2025**, *7*, 21–28. [CrossRef]

19. Gunawan, A.A.N.; Windiarti, I.S.; Nasution, U.B.; Utomo, S.T.; Asuhadi, S. Investigating the role of digital transformation, digital knowledge management and digital innovation on sustainable performance (SDG) of SMES. *J. Lifestyle SDGs Rev.* **2024**, *4*, e02047. [CrossRef]
20. Windiarti, I.S.; Miftahurrisqi, M. Perencanaan implementasi komputasi awan pada infrastruktur Universitas Muhammadiyah Palangkaraya. *J. Sains Komput. Dan Teknol. Inf.* **2022**, *4*, 59–64. [CrossRef]
21. Miftahurrisqi, M.; Windiarti, I.S.; Haryanto, D. Edukasi dan Peningkatan Kompetensi It-Security Dan E-Commerce Bagi Mahasiswa Ma'had Asy-Syafi'i Universitas Muhammadiyah Palangkaraya. *J. Martabe* **2021**, *4*, 963–969.
22. Sommerville, I. *Software Engineering*, 10th ed.; Pearson Education Limited: Essex, UK, 2016.
23. Al-Karkhi, M.I.; Rządkowski, G. Innovative machine learning approaches for complexity in economic forecasting and SME growth: A comprehensive review. *J. Econ. Technol.* **2025**, *3*, 109–122. [CrossRef]
24. Yang, H.; Yu, L. A method of forecasting cross-border e-commerce stocking for SMEs based on demand characteristics and sequence trends under sustainable development strategy. *Int. J. Comput. Syst. Eng.* **2023**, *7*, 57–66. [CrossRef]
25. Zellner, M.; Abbas, A.E.; Budescu, D.V.; Galstyan, A. A survey of human judgement and quantitative forecasting methods. *R. Soc. Open Sci.* **2021**, *8*, 201187. [CrossRef] [PubMed]
26. Hyndman, R.J.; Athanasopoulos, G. *Forecasting: Principles and Practice*, 3rd ed.; OTexts: Melbourne, Australia, 2021.
27. Sánchez, E.; Calderón, R.; Herrera, F. Artificial intelligence adoption in SMEs: Survey based on TOE–DOI framework, primary methodology and challenges. *Appl. Sci.* **2025**, *15*, 6465. [CrossRef]
28. Makridakis, S.; Petropoulos, F.; Spiliotis, E. Introduction to the M5 forecasting competition Special Issue. *Int. J. Forecast.* **2022**, *38*, 1279. [CrossRef] [PubMed]
29. Koutsandreas, D.; Spiliotis, E.; Petropoulos, F.; Assimakopoulos, V. On the selection of forecasting accuracy measures. *J. Oper. Res. Soc.* **2022**, *73*, 937–954. [CrossRef]
30. Ameen, S.; Aslam, M.; Ahmad, I.; Ali, I. Enhancing Supply Chain Resilience in Developing Country SMEs through Machine Learning-Based Demand Forecasting: An Empirical Study. *Crit. Rev. Soc. Sci. Stud.* **2025**, *3*, 3050–3088. [CrossRef]