International Journal of Management Science and Information Technology
IJMSIT

E-ISSN: 2774-5694 P-ISSN: 2776-7388 OPEN ACCESS

Volume 6 (2), July-December 2026, 1903-1913
DOI: https://doi.org/10.35870/ijmsit.v6i2.8277

Development of Intelligent Decision Support System Based on Quadrant Analysis, Time Series Trend Analysis, and Automatic Planogram Generation for Vending Machine Product Optimization

Rizaldi Putra [1*], Syaban Maulana [2], Tessalonika Audry Polnaya [3], Muhammad Zaky Fahriansyah [4]
[1*,2,3,4] Digital Business Study Program, Politeknik Takumi, Bekasi Regency, West Java Province, Indonesia

Email: rizaldi.rip@takumi.ac.id [1*], syaban.sbm@takumi.ac.id [2], 2413010004@takumi.ac.id [3], 2413010008@takumi.ac.id [4]

Article history:
Received August 2, 2026
Revised August 16, 2026
Accepted August 20, 2026

Abstract

Product management in a vending machine business requires fast and data-driven decision-making to increase sales effectiveness and profitability. However, decision-making related to price adjustments, product bundling, product replacements, and product arrangement on vending racks is still mostly done manually based on the manager's experience, so it has the potential to produce less than optimal decisions. This research aims to develop an Intelligent Decision Support System that is able to produce business strategy recommendations through the integration of Quadrant Analysis, Time Series Trend Analysis, and Automatic Planogram Generation. The research data was obtained from the results of exporting the vending machine transaction database imported into the application in CSV or Excel format, so that the system does not depend on direct integration with the Application Programming Interface (API). Quadrant Analysis is used to group products based on sales performance and profit contribution, while Time Series Trend Analysis is used to evaluate historical sales trends as a support for decision validation, rather than as a sales prediction method. The results of the second analysis were processed using a rule-based decision engine mechanism to produce recommendations in the form of price adjustments, product bundling, maintaining or replacing products, and compiling an automatic planogram based on product performance priorities. The resulting planogram can still be adjusted manually by the user so that it still provides flexibility in operational decision-making. In addition, the system presents profit analysis based on product, machine, and location as the basis for business evaluation. The resulting artifacts are in the form of a decision support system application that not only presents data visualization, but also automatically generates strategic recommendations to help managers improve the effectiveness of product management in the vending machine business.

Keywords:
Decision Support System; Business Analytics; Quadrant Analysis; Time Series Trend Analysis; Automatic Planogram; Vending Machine.

1. INTRODUCTION

The development of the modern retail industry has made vending machines a form of self-service technology that plays an essential role in providing practical and rapid transaction access (Hilmi et al., 2024; Sharma, 2026). Functioning as hyper-local micro-fulfillment centers, vending machines operate independently without requiring on-site staff (Mehmood et al., 2023; Sharma, 2026). However, the storage capacity of vending machine slots is inherently limited (Ohanjanian & Varahram, 2026; Sharma, 2026). Allocating slow-moving products to these limited slots reduces the economic value of the available space and decreases overall machine profitability until the next replenishment cycle (Ohanjanian & Varahram, 2026; Sharma, 2026).

Therefore, determining the optimal product assortment and designing an effective shelf layout (planogram) are critical factors for maximizing sales performance and operational profitability (Ohanjanian & Varahram, 2026; Vella, 2026).

Although transaction data are generally recorded digitally, operational decisions such as price adjustments, product bundling, product replacement (swap-out), and planogram preparation are still predominantly based on managerial intuition and empirical experience rather than systematic analytical approaches (Nemoto, 2025; Sharma, 2026). The absence of quantitative data analysis increases the risk of overstocking, resulting in excessive inventory and product expiration, as well as understocking, which leads to lost sales opportunities and lower customer satisfaction (Laudon & Laudon, 2004). Furthermore, implementing data-driven operational systems is often constrained by technical complexity and the high cost of integrating Application Programming Interfaces (APIs) directly into transactional databases (Ahmed, 2022).

To address these challenges, the Intelligent Decision Support System (IDSS) provides an intelligent framework that integrates quantitative analysis of historical data with rule-based reasoning to support complex decision-making processes (Changlin & Yufen, 2017). By combining structured data processing with multidimensional analysis through Online Analytical Processing (OLAP), IDSS enables comprehensive business performance evaluation (Li et al., 2024). In this study, the proposed system processes structured transaction data exported in CSV or Excel format, allowing practical and flexible implementation without requiring direct API integration (Ahmed, 2022; Wiratama & Bagioyuwono, 2023).

Within the proposed IDSS, Quadrant Analysis is employed to classify products according to sales volume and profit margin contribution (Hermanto et al., 2023). Subsequently, Time Series Trend Analysis using the Exponentially Weighted Moving Average (EWMA) method is applied to evaluate historical sales momentum as a decision validation tool rather than a forecasting model (Lucas & Saccucci, 1990). The outputs from both analytical methods are processed by a rule-based decision engine to generate strategic recommendations, including price adjustments, product bundling, and decisions to retain or replace products (Changlin & Yufen, 2017; Hermanto et al., 2023). These recommendations subsequently drive the Automatic Planogram Generation module, which organizes product placement based on a hierarchy of product performance priorities (Ohanjanian & Varahram, 2026; Pagidoju & Agarwal, 2026).

To ensure operational practicality, the automatically generated planograms remain editable by managers through a human-in-the-loop approach, allowing adjustments based on physical shelf constraints such as package dimensions and spiral configurations (Grzybowska et al., 2020; Lin et al., 2011). By providing multidimensional profit visualization across products, vending machines, and locations, the proposed IDSS is expected to improve product management effectiveness while enhancing the profitability and operational efficiency of vending machine businesses (Li et al., 2024; Ohanjanian & Varahram, 2026).

2. RESEARCH METHOD

2.1. Intelligent Decision Support System (IDSS) Pipeline and Architecture

The Intelligent Decision Support System (IDSS) was developed by integrating the quantitative analytical capabilities of Decision Support Systems (DSS) with rule-based reasoning to address complex operational decision-making problems (Changlin & Yufen, 2017). The IDSS architecture comprises several core components, including the database management subsystem, model management subsystem, method base, knowledge base subsystem, inference engine, problem processing system, and user interface subsystem (Changlin & Yufen, 2017; Mehmood et al., 2023; Sharma, 2026). Within this architecture, raw transaction data are extracted from the operational database, cleansed, and transformed through the Extract, Transform, Load (ETL) process into a structured data warehouse to support analytical processing (Changlin & Yufen, 2017; Ahmed, 2022). Subsequently, the structured data are processed using multidimensional Online Analytical Processing (OLAP) integrated with a model base to provide input for a rule-based decision engine, enabling the automatic generation of business strategy recommendations (Awamleh et al., 2024; Changlin & Yufen, 2017; Li et al., 2024).

2.2. Data Acquisition and Data Pre-processing

The research data were obtained from exported vending machine transaction records in structured CSV or Excel format (Power & Heavin, 2017). The use of structured file inputs enables the proposed system to operate flexibly without requiring direct integration with complex and costly Application Programming Interfaces (APIs) (Ahmed, 2022; Power & Heavin, 2017). The raw transaction dataset contains detailed information, including transaction timestamps, product names (or European Article Number [EAN]), product categories, transaction prices, vending machine identifiers, location types, and shelf and slot positions (Power & Heavin, 2017). Before analysis, the transaction data undergo a pre-processing stage consisting of the following steps:

a. Data Cleansing & Attribute Handling, cleans transaction records of missing values and aligns product SKU naming inconsistencies, where product names are used as the primary product identification (Power & Heavin, 2017).

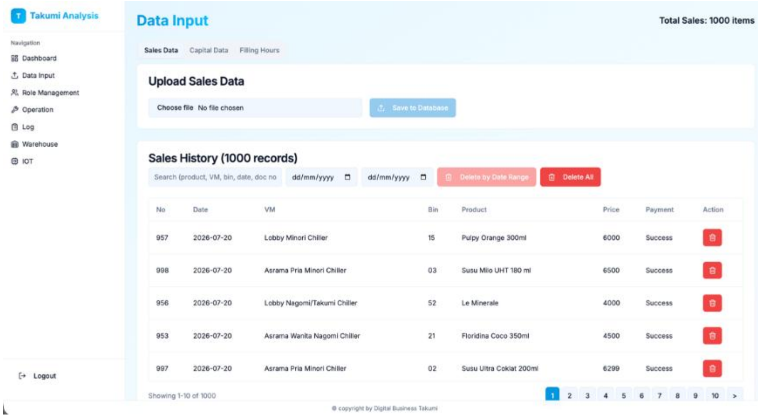


Figure 1. Data import and cleaning process

b. Weekly Panel Construction: Raw transaction data is aggregated into a weekly periodic panel form per combination of vending machines and products (machine-product-week grain) (Power & Heavin, 2017).

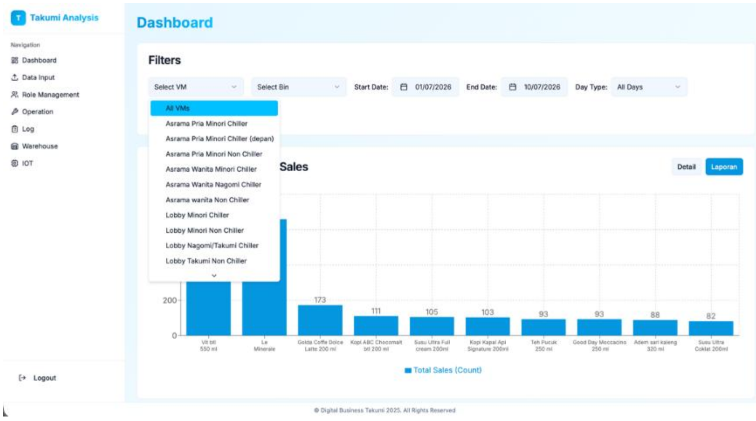


Figure 2. Sales chart by time and machine

2.3. Quantitative Data Analysis Methods

The system runs two quantitative analysis techniques independently to evaluate product performance based on the panel's historical data.

2.3.1. Quadrant Analysis

Quadrant Analysis maps all active products into a four-quadrant matrix based on two primary performance dimensions, namely sales volume and profit contribution (Hermanto et al., 2023; Power & Heavin, 2017).

a. Quadrant I (High Sales, High Profit / Stars): High-performance superior products with large sales volumes and high profit margin contributions.
b. Quadrant II (Low Sales, High Profit / Cash Cows): Products with relatively low sales volume but generating large profit margins per unit.
c. Quadrant III (High Sales, Low Profit / Volume Drivers): Products that sell fast (fast-moving) but contribute a small profit margin per unit.
d. Quadrant IV (Low Sales, Low Profit / Slow Movers): Weak performing products with slow sales volume and minimal profit contribution.

This quadrant grouping is influenced by the context of the location category, where consumer preferences and variations in product mix differ significantly between operational environments (Power & Heavin, 2017). Here are the mathematical formulations and calculation steps of Quadrant Analysis using 2 main variables: Sales (Variable X) and Profit (Variable Y).

a. Variable Definition
Suppose there are n types of products (i=1,2,3....,n):
- Xi (Sales): Sales volume (number of units cut/sold) or Total Revenue of the ith product.
- Yi (Profit): The Percentage of Profit Margin (%) or Total Profit (Profit) of the ith product.

b. Cutoff Point. To divide the data into 4 quadrants, the center/boundary value of the cartesian axis line is determined in the form of the Mean of the entire product population:

1. **Rata-rata Penjualan (X):**

$$\bar{X} = \frac{\sum_{i=1}^{n} X_i}{n}$$

2. **Rata-rata Keuntungan ($\bar{Y}$):**

$$\bar{Y} = \frac{\sum_{i=1}^{n} Y_i}{n}$$

Figure 3. Quadrant analysis formula for two variables

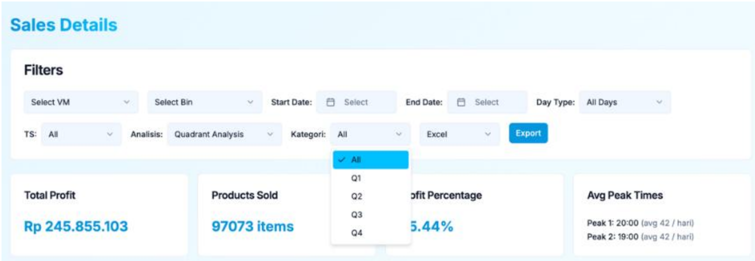
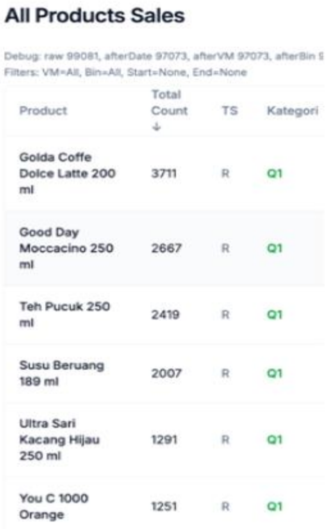


Figure 4. Q1–Q4 quadrant analysis filter

The system will calculate based on sales and profit and group products based on quadrants as shown in the following figure:



Product	Total Count ↓	TS	Kategori
Golda Coffe Dolce Latte 200 ml	3711	R	Q1
Good Day Moccacino 250 ml	2667	R	Q1
Teh Pucuk 250 ml	2419	R	Q1
Susu Beruang 189 ml	2007	R	Q1
Ultra Sari Kacang Hijau 250 ml	1291	R	Q1
You C 1000 Orange	1251	R	Q1

Figure 5. Filtered results of the quadrant analysis calculation

2.3.2. Time Series Trend Analysis

Time Series Trend Analysis is used specifically as a tool to validate historical sales movements (sales momentum), not as a model for predicting pure sales figures (Power & Heavin, 2017). Trend evaluation was carried out by calculating exponentially weighted moving average (EWMA) indicators across various time horizons (4, 8, and 13 weeks), short-term to long-term momentum ratios, and historical sales movement trends (Power & Heavin, 2017).

The analysis output classifies the direction of product movement into three trend categories, namely Upward, Stable, or Downward (Power & Heavin, 2017).

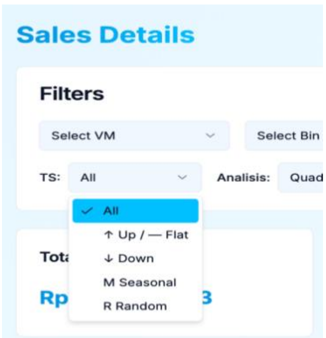


Figure 6. filter time series trend analysis

From the image above, the combination of quadrant analysis and time series will help make decisions to maintain, provide discounts or replace products in quadrant 4 category. The image below shows that some products with a positive trend will be maintained, products that are flat or down will be given discounts to increase sales and down products will be replaced with products that are bar.

All Products Sales

Debug: raw 99081, afterDate 97073, afterVM 97073, afterBin 97073, aq
Filters: VM=All, Bin=All, Start=None, End=None

Product	Total Count ↓	TS	Kategori
Kalio chips 28 gr	138	↑	Q4
Pop Cron Oisi Keju 20 gr	56	↑	Q4
Nabati wafer white 50gr	21	↑	Q4
Pop Mie Baso Kecil 2 gr	18	↑	Q4
Kacang Polong Ori Nyemil Time	12	↑	Q4
RITZ Cheese	10	—	Q4
Pop Mie Kuah Dower 75 gr	6	↑	Q4

Figure 7. Q4 product uptrend

2.3.3. Rule-Based Decision Engine Design

The rule-based decision engine applies if–then reasoning to interpret the combined outputs of Quadrant Analysis and Time Series Trend Analysis, enabling consistent and explainable decision-making (Changlin & Yufen, 2017; Power & Heavin, 2017). Based on predefined business rules, the engine automatically generates strategic recommendations, including pricing adjustments, product bundling strategies, and decisions to retain or replace products (Changlin & Yufen, 2017; Power & Heavin, 2017).

a. Pricing Adjustment: Recommended for Quadrant III (Volume Drivers) products that have a stable or increasing trend of sales movements to optimize profit margins without sacrificing sales volume (Power & Heavin, 2017).

All Products Sales

Debug: raw 99081, afterDate 97073, afterVM 97073, afterBin 970
Filters: VM=All, Bin=All, Start=None, End=None

Product	Total Count ↓	TS	Kategori
Pop Mie Mini Ayam Bawang 40gr	381	R	Q3
Floridina Coco 350ml	312	R	Q3
Buavita Rasa Jambu	268	R	Q3
Buavita Rasa Leci 245ml	261	R	Q3
Buavita Rasa Orange	256	R	Q3
Susu Ultra full cream 250 ml	192	R	Q3
Green Sands Lime Apple 330 ml	122	R	Q3

Figure 8. products with quadrant 3

b. Product Bundling: Combining package offerings between Quadrant III (fast-moving, low-margin) products with Quadrant I or Quadrant II (high-margin) products to encourage consumer purchasing power towards high-margin products (Power & Heavin, 2017; Laudon & Laudon, 2004).

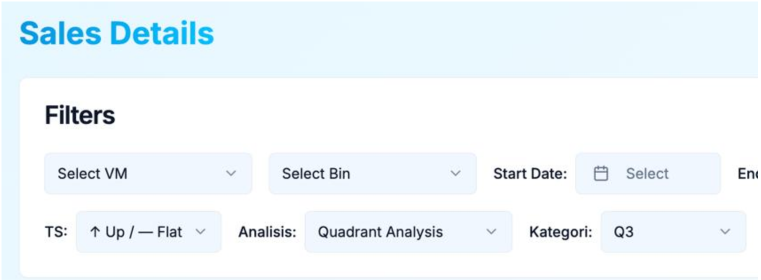


Figure 9. analysis quadrant 3 and uptrend time series calculation filters

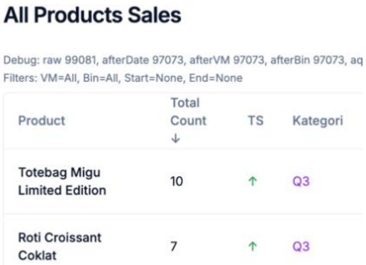


Figure 10. Quadrant 3 image with Uptrend Time Series

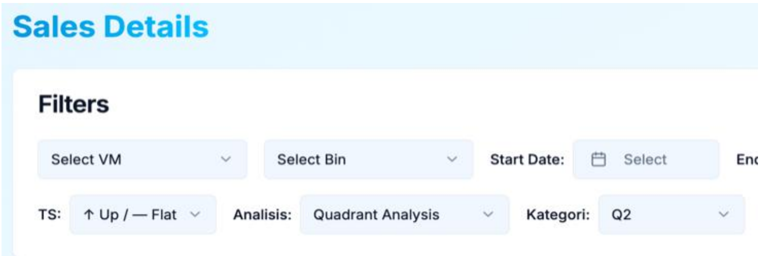


Figure 11. analysis quadrant 2 and uptrend time series calculation filters

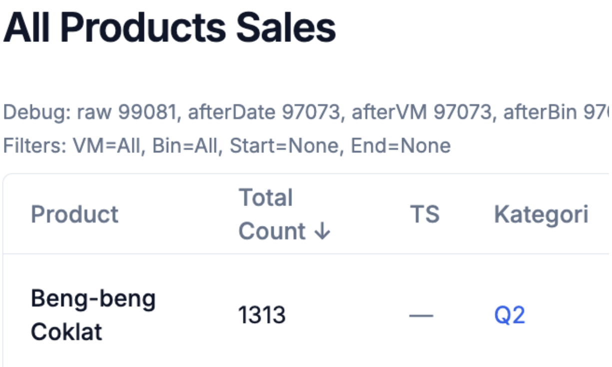


Figure 12. Quadrant 2 image with Uptrend Time Series

From the two images above, the data shows Q3 uptrend with Q2 Uptrend analysis results and system recommendations to be able to make a croissant bread bundling program with chocolate beng beng beng So are other bundling combinations.

Figure 13. The product's chart shows an upward trend

c. Keep vs. Swap-Out: Maintain a well-performing product (Quadrant I and Quadrant III are trending positively) and recommend swap-out for Quadrant IV products that are underperforming and showing a downward trend in sales (Power & Heavin, 2017).
   1) Upward:
      - Conditions: Short-term sales/EWMA indicators are significantly higher than long-term (Momentum Ratio $>1+\varepsilon$).
      - Meaning: The product is gaining traction (Changlin & Yufen, 2017; Sharma, 2026).

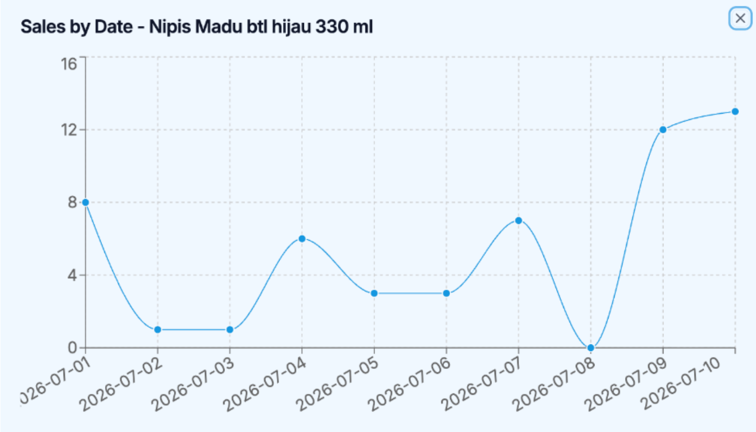


Figure 14. The product's chart shows an upward trend

   2) Stable:
      - Conditions: The short-term sales indicator/EWMA is relatively balanced or within the tolerance threshold range compared to the long term (Momentum Ratio ≈ 1).
      - Meaning: The sales rate of the product is consistent and does not experience significant spikes or declines (Changlin & Yufen, 2017).
   3) Downward:
      - Conditions: Short-term sales indicators/EWMAs are significantly lower than long-term (Momentum Ratio $<1-\varepsilon$).
      - Meaning: The product experiences a decline in performance and loss of sales momentum (losing traction / declining) (Changlin & Yufen, 2017; Sharma, 2026).

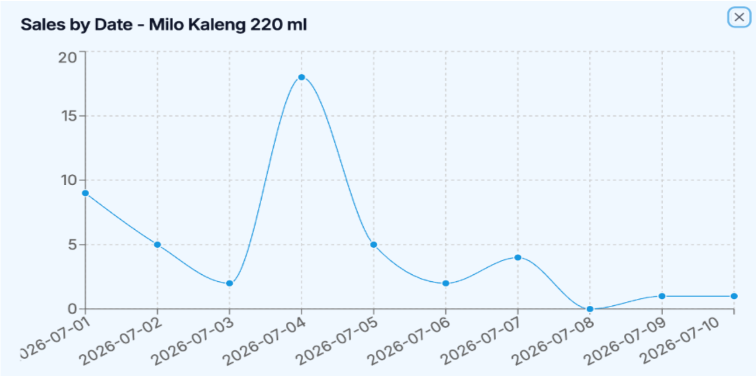


Figure 15. The product's chart shows a downward trend.

2.3.4. Planogram Automation and Operational Flexibility (Human-in-the-Loop)

Once the priority of the product recommendation is established, the system executes the Automatic Planogram Generation module:

a. Performance Priority-Based Preparation: Allocating slot positions and vending machine racks based on the ranking of combined quadrant priorities and movement trends, taking into account the physical suitability of slot widths (standard, wide, double) (Power & Heavin, 2017).
b. Operational Flexibility (Human-in-the-Loop): Given the physical constraints in the field such as packaging dimensions, slot capacity, and spiral type variations, the system provides a planogram editor interface (Power & Heavin, 2017). This interface allows managers to make manual layout adjustments (drag-and-drop) before the planogram is operationally applied to the refill process (Power & Heavin, 2017).
c. Handling Cold-Start Conditions: In new machine units or locations that do not have an adequate local transaction history, the system uses a similarity-based transfer mechanism by referring to the sales performance of a cohort of similar machines operating in a similar location reference machine environment (Power & Heavin, 2017).

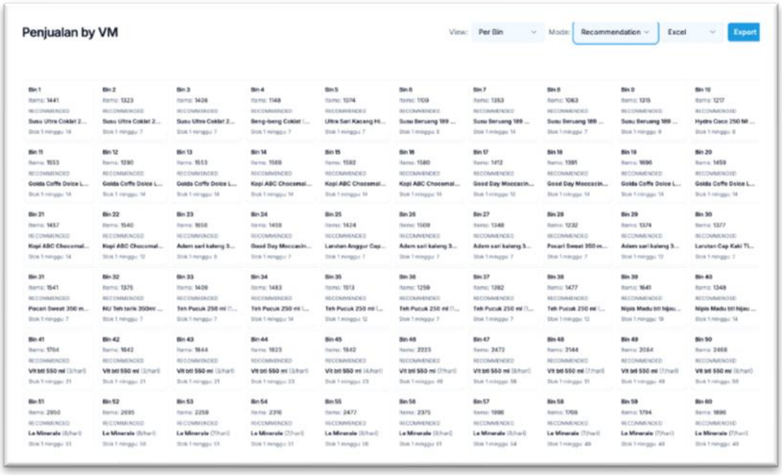


Figure16. Automated planogram based on system recommendations

The image above shows the automatic system of arranging products based on the bin on the Vending Machine.

2.3.5. Multi-Dimensional Visualization and System Evaluation

The system is equipped with a visualization dashboard that presents a multi-dimensional analysis of business profits and performance (Power & Heavin, 2017).

a. Product-Based Analysis: Evaluate profitability and sales volume per product SKU.
b. Machine-Based Analysis: Evaluation of effectiveness and profitability between vending machine units.
c. Location-Based Analysis: Performance mapping based on operational location categories (Power & Heavin, 2017).

The evaluation of the IDSS artifact was carried out through system functionality testing (black-box testing) on all application modules as well as testing the accuracy of strategic recommendation logic flows (decision support capability) based on historical data scenarios (Power & Heavin, 2017; Ahmed, 2022).

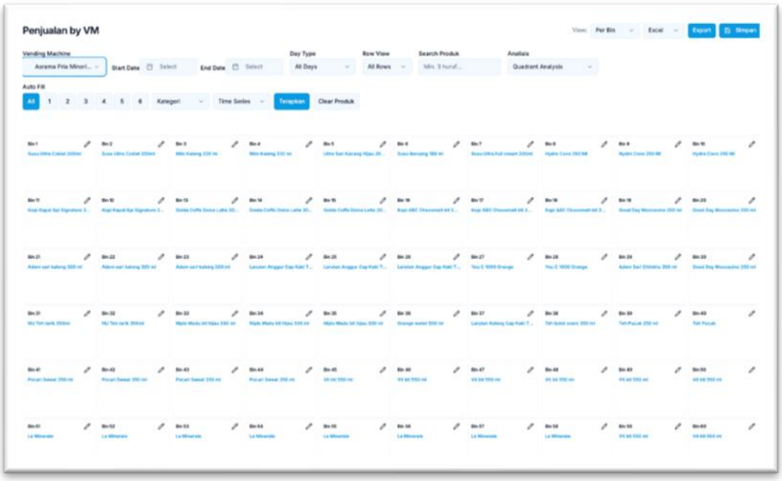


Figure 17. Automated planogram based on location and product

The image above shows the sorting system based on product analysis, machine and location. The picture above shows the machine in the men's dormitory. Operators in the field will see a virtual arrangement based on analysis to be applied in the field as a reference for product preparation or planograms. Here's what the vending filling operator looks like.

Figure 18. Automated visual planogram for operators

3. RESULTS AND DISCUSSION

3.1. Decisions Based on Integration of Quadrant Analysis and Time Series Trend Analysis

The test results show that the integration of Quadrant Analysis and Time Series Trend Analysis is able to produce much more accurate and precise operational decisions than if relying only on one of the manager's manual methods or intuition

Quadrant Analysis provides a static mapping of the product's performance position based on two main variables (sales volume and profit margin). However, the certainty of business decisions is not enough based only on the position of the static quadrant, but requires validation of the historical sales momentum provided by Time Series Trend Analysis.

The combination of these two analyses prevents premature product elimination. For example, a product that is statically in the weak performance category can revisit its trend momentum before a final decision is made. This significantly increases the effectiveness of rack slot allocation and pricing strategy on vending machines.

3.2. Planogram Allocation Strategy and Price Adjustment (Quadrants I, II, and III)

Based on the outputs of the rule-based decision engine, the allocation of shelf layouts (planograms) and pricing strategies for products classified in Quadrants I, II, and III is governed by the logic of physical layout priority as follows:

a. Quadrant I (High Sales, High Profit / Stars): Products in Quadrant I are the main contributors to business revenue and profit. Therefore, the decision engine recommends placing Quadrant I products in the most strategic position in the vending machine (such as an eye-level position). Products in this category are also allocated with the greatest number of bins or slots (multiple facings) to prevent the risk of stockout between refill intervals.
b. Quadrant II (High Sales, Low Profit / Volume Drivers): Products in Quadrant II have a high sales volume but low profit margin contribution. This product is placed next to the Quadrant I area with a smaller number of bins than Quadrant I. To optimize its economic value, the system recommends a gradual adjustment of price increases to increase profit margins without sacrificing the attractiveness of high sales volumes.
c. Quadrant III (Low Sales, High Profit / Cash Cows): Products in Quadrant III have high profit margins but the sales volume is still relatively low. In the planogram, Quadrant III products are placed in an adjacent position between Quadrant I and Quadrant II to take advantage of the overflow of consumer attention (visual spillover effect) The recommended business strategy is to reduce the selling price (price reduction/discount), considering that the profit margin of this product is still very thick, so the price decrease is expected to stimulate a surge in sales volume.

3.3. Handling of Quadrant IV Products Based on Time Series Trend Analysis (Slow Movers)

Products that fall into Quadrant IV (Low Sales, Low Profit / Slow Movers) require special handling because they have the potential to empty the economic value of shelf slots. The system does not directly rotate all Quadrant IV products, but conducts advanced evaluations based on Time Series Trend Analysis (EWMA and historical momentum movement) indicators:

a. Quadrant IV with Upward Trend: Quadrant IV products that show a positive sales movement trend (Upward) are maintained (Keep) in the vending machine. The trend of increasing sales indicates that the product is gaining traction and has the potential to move to a higher quadrant in the coming period.
b. Quadrant IV with Downward Trend: Quadrant IV products that show a downward trend in sales (Downward) are decided to be replaced (Swap-Out). Before being replaced with a new candidate product, the system recommends providing a special price discount to deplete the remaining stock (clearance stock) in the slot, thereby minimizing the risk of losses due to expired products or capital buildup. Once the stock is depleted, the slots are allocated to replacement products based on recommendation priority

3.4. The Impact of Strategic Decisions on the Effectiveness of Vending Machine Management

The application of IDSS business logic rules that combine Quadrant Analysis and Time Series Trend Analysis has a positive impact on the manager's operational efficiency. With automated shelf layout guidance and measurable price action recommendations, managers can reduce reliance on intuitive-based speculative decisions. This approach has been proven to be able to optimize the economic value of each slot vending machine, accelerate the stock rotation of poorly performing products, and increase the overall profitability of the machine unit in a sustainable manner.

4. CONCLUSION

Based on the results of design, testing, and analysis that has been carried out, it can be concluded that the Intelligent Decision Support System (IDSS) application along with the analysis methods developed has proven to be quite effective in helping business strategy decision-making for vending machine product management. The effectiveness of this system is demonstrated by some of the following key achievements:

a. Improved Strategic Decision Accuracy: Integrating Quadrant Analysis and Time Series Trend Analysis into a rule-based decision engine successfully overcomes the limitations of manual decisions based on managerial intuition. The combination of static quadrant performance evaluation (sales and profit margins) with historical trend validation (EWMA) has been proven to be able to prevent premature product elimination errors and produce precise business action recommendations, such as price adjustments and product bundling.
b. Automatic Planogram: Automating the preparation of planograms based on the product priority hierarchy—by allocating the most slots in the most strategic positions for Quadrant I products, increasing prices in Quadrant II, providing discounts/promotions in Quadrant III, and rotating negative Quadrant IV products—is able to optimize the utilization of limited shelf slot capacity.
c. Operational Flexibility and Practicality: The use of structured data entry schemes (CSV or Excel) without reliance on Application Programming Interface (API) integration directly provides easy system adoption for managers in addition, the human-in-the-loop approach to the planogram editor interface provides flexibility for managers to adjust the physical layout according to real constraints in the field (such as packaging size and spiral type variations).
d. Multidimensional Business Visualization: Visualization dashboards that present profit analysis by product, machine, and location provide a comprehensive picture of business performance to support fast, scalable operational evaluations

REFERENCES

Ahmed, M. S. (2022). Study on Data Warehousing Applications: An Analytical Tool for Decision Support System. Recent Advances in Mathematical Research and Computer Science Vol. 8, Book Publisher International (a part of SCIENCEDOMAIN International), 45-54, 2022, https://dx.doi.org/10.9734/bpi/ramrcs/v8/2400C

Awamleh, F. T., Bustami, A., Alarabiat, Y., & Sultan, A. (2024). Data-driven decision-making under uncertainty: Investigating OLAP's mediating role to leverage business intelligence analytics for entrepreneurship. Journal of Systems and Great Sciences, 14, 523–1818. https://doi.org/10.33168/jsms.2024.0822

Changlin, H., & Yufen, L. (2017). A survey of intelligent decision support system. In 2017 7th International Conference on Applied Science, Engineering and Technology (ICASET 2017) (pp. 201-206). Atlantis Press. https://doi.org/10.2991/icaset-17.2017.38

Czerniachowska, K., Lutosławski, K., & Fojcik, M. (2022). Heuristics for shelf space allocation problem with vertical and horizontal product categorization. Procedia Computer Science, 207, 195–204. https://doi.org/10.1016/j.procs.2022.09.052

Grzybowska, H., Kerferd, B., Gretton, C., & Waller, S. T. (2020). A simulation-optimisation genetic algorithm approach to product allocation in vending machine systems. Expert Systems with Applications, 145, 113110. https://doi.org/10.1016/j.eswa.2019.113110

Hermanto, E. A., Gemintang, S. A., Ariansyah, R., & Giovanny, M. A. (2023). Analisis Perbandingan Penerapan Business Intelligence di Indonesia Menggunakan Metode Systematic Literature Review. Jurnal Teknologi Informasi, 4(2), 345-354. https://doi.org/10.46576/djtechno.v4i2.3412

Hilmi, N. F., Abdillah, A. R., Maulana, P. S., & Prakoso, M. S. B. (2024). The application of business intelligence to vending machine sales in Central New Jersey USA using Tableau. J-Intech (Journal of Information and Technology), 12(1), 148–157. https://doi.org/10.32664/j-intech.v12i1.1275

Laudon, K. C., & Laudon, J. P. (2004). Management information systems: Managing the digital firm. Pearson Education.

Li, X., Shen, Q., & Yang, T. (2024). Design and optimization of multidimensional data models for enhanced OLAP query performance and data analysis. Applied and Computational Engineering, 69(1), 161–166. https://doi.org/10.54254/2755-2721/69/20241503

Lin, F.-C., Yu, H.-W., Hsu, C.-H., & Weng, T.-C. (2011). Recommendation system for localized products in vending machines. Expert Systems with Applications, 38(8), 9129–9138. https://doi.org/10.1016/j.eswa.2011.01.051

Lucas, J. M., & Saccucci, M. S. (1990). Exponentially Weighted Moving Average Control Schemes: Properties and Enhancements. Technometrics, 32(1), 1–12. https://doi.org/10.1080/00401706.1990.10484583

Marinelli, L., Fiano, F., Gregori, G. L., & Daniele, L. M. (2021). Food purchasing behaviour at automatic vending machines: The role of planograms and shopping time. British Food Journal, 123(5), 1821–1836. https://doi.org/10.1108/BFJ-02-2020-0107

Mehmood, U., Bashir, A. K., Rabie, K., Broderick, J., & Davies, S. (2023). Vending machine product demand prediction using machine learning algorithms. In Proceedings of the IEEE International Symposium on Networks, Computers and Communications (ISNCC) (pp. 1–6). IEEE.

Nemoto, G. (2025). Research on decision-making methods under uncertain information: Assortment optimization for vending machines (Doctoral dissertation). Japan Advanced Institute of Science and Technology.

Ohanjanian, D., & Varahram, S. (2026). Data-driven decision support system for vending machine planograms using machine learning and heuristic algorithms (Master's thesis). Uppsala University.

Pagidoju, R. T., & Agarwal, S. (2026). Cloud-native generative AI for automated planogram synthesis: A diffusion model approach for multi-store retail optimization (arXiv Preprint No. arXiv:2601.00527).

Perfetti, A., Pietrini, R., Scarpi, D., & Gistri, G. (2025). Snack dilemma: how vending machines influence choice of virtue and vice foods. Journal of Retailing and Consumer Services, 87, 104369. https://doi.org/10.1016/j.jretconser.2025.104369

Power, D. J., & Heavin, C. (2017). Decision support, analytics, and business intelligence. Business Expert Press.

Sharma, A. (2026). Intelligent vending machines market size, share & trends analysis report by machine type, by product type, by application and by region forecasts, 2026–2034. Straits Research.

Vella, H. (2026). How your retail planogram benefits from automation and new technology. Verizon Business Resources.

Wiratama, J., & Bagioyuwono, M. A. (2023). Improving the data management: ETL implementation on data warehouse at Indonesian vehicle insurance industry. International Journal of Science, Technology and Great, 4(5), 1256–1268. https://doi.org/10.46729/ijstm.v4i5.936