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A Web-Based Decision Support System for Inventory Procurement Optimisation Using Pareto Analysis

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ABSTRACT

Existing research and practical applications of multi-objective optimization in this domain continue to rely mainly on manual Pareto analysis. Typically, decision makers analyze trade-off curves or a collection of candidate solutions before making subjective configuration choices. This method is time-consuming, difficult to replicate, and subject to bias or inconsistency among evaluators. Furthermore, many publications stop at creating the Pareto front without giving a systematic mechanism for automated selection or assessing the effectiveness of the produced front in comparison to alternative tactics. Data for fast-moving product categories with high profit margins can be processed in a computerized application. These two parameters will provide the best recommendations according to the Pareto principle, which states that 80% of the best income comes from 20% of sources. Pareto Method optimization has proven to narrow the focus of work on the parts that have a significant effect (benefit) for the pharmacy. The manual process used before the research was conducted resulted in one item recommendation in 6 minutes and 20 seconds, while the computerized DSS could process a large amount of item data in just 3 minutes and 15 seconds, with an average gross profit for the top 10 recommended items of 32.1%. This study presents an automated Pareto optimization and selection methodology, which eliminates the need for manual inspection. The system not only creates candidates for Pareto-optimal solutions, but also ranks and selects them based on quantitative criteria. In addition, the framework includes comparative benchmarking, which allows for performance evaluation against baseline methodologies, heuristics, or existing decision procedures. This results in an objective, repeatable, data-driven decision pipeline.

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1. INTRODUCTION

Current approaches for pharmacy inventory decision making usually rely on manual evaluation or the use of generic optimisation technologies that necessitate significant human interpretation. Such procedures are time-consuming, difficult to replicate, and prone to subjective bias, particularly when decision makers are left to evaluate Pareto trade-offs without formal direction. Despite the availability of multi-objective optimisation approaches, many previous studies only produce candidate solutions without offering an automated, operational mechanism for selecting and validating them in real-world procurement scenarios. This highlights a research gap in combining Pareto analysis with systematic, domain-specific decision support and quantitative benchmarking. Inefficiencies in this area often manifest as limited varieties of drug formulations, cases of overstocking that lead to expiration, or conversely, understocking which results in lost sales[4], [5].

To fill this gap, the proposed system introduces an automated Pareto-based optimisation and ranking framework embedded within a web-based decision support environment for pharmacy procurement. The novelty of this work lies in transforming Pareto results into actionable recommendations through quantitative selection rules and comparative performance evaluation, to improve efficiency, consistency, and transparency beyond what manual or generic tools can provide. The growth of the pharmacy industry has been notable in recent years. Data from the Central Statistics Agency of East Java Province highlights a significant increase in the number of pharmacy health facilities. Specifically, in Sumenep Regency, the number of pharmacies increased by 41.67% between 2019 and 2021. This rapid expansion indicates a thriving market but also implies fiercer competition and more complex logistical challenges for individual pharmacy units to survive and remain profitable[6].

A primary consequence of these disruptions was the widespread issue of stock shortages. A survey of 96 pharmacists revealed that 70.8% experienced issues with understocking of drugs and medical devices[6]. Among the various inventory problems, understocking is identified as the most serious issue impacting business profitability[5]. Without the right items in stock, pharmacies cannot fulfill patient needs, leading to dissatisfaction and reduced revenue[3].

In many pharmacies, including the subject of this study, the procurement process is still conducted using conventional manual methods. This typically involves recording needs in a "Defecta Book" or a "Refusal Book," and relying on handwritten notes from patient orders[2]. The determination of order quantities is often based on the pharmacist's intuition or subjective prediction. This manual approach is prone to human error, time-consuming, and lacks the precision required for optimal financial investment[4].

To address these inefficiencies, scientific methods such as Pareto Analysis (often referred to as the 80/20 rule) have been applied in inventory control. The Pareto principle suggests that approximately 80% of profits or results are derived from only 20% of causes or products[8], [9], [10]. In the context of a pharmacy, this means identifying the "Fast-Moving" items that generate the most revenue is crucial. These items must be ordered carefully to align with sales capabilities and financial constraints[11], [12].

While Pareto Analysis is theoretically sound, its manual application is laborious. Processing large datasets of sales history to calculate profit margins and sales frequency manually is inefficient. This creates a need for technological intervention. A computerized Decision Support System (DSS) can process, calculate, sort, and display data rapidly using Structured Query Language (SQL) commands, offering response times of less than one second[13], [14].

This research proposes the development of a web-based Decision Support System named "SIROP" (*Sistem Informasi Rekomendasi Pengadaan*) to optimize the use of the Pareto Method. Unlike previous manual attempts, this system automates the identification of high-margin and fast-moving products[11], [12]. It is designed to provide accurate, transparent, and accountable recommendations to pharmacists, ensuring that procurement decisions are data-driven rather than intuitive[14]. The objectives of this study include: defining the problem, data collection, system design, implementation, and testing.

To validate the effectiveness of the proposed system, this study employs a comparative approach. The results generated by the SIROP application are compared not only against manual methods but also against Rapid Miner, a prominent data science tool. The comparison utilizes K-Means clustering and Pareto-Rank algorithms within Rapid Miner to benchmark the accuracy and profitability of the recommendations produced by the custom-built web application[15].

Ultimately, this study aims to demonstrate that a computerized SPK can significantly reduce processing time and increase Gross Profit Margin (GPM). Preliminary results indicate the system can generate recommendations in 3 minutes and 15 seconds with a GPM of 32.1%, outperforming other methods. This technological integration supports the pharmacist’s professional role by handling the computational burden of planning, thereby minimizing human error and maximizing business efficiency.

2. RESEARCH METHOD

This research adopts a qualitative approach focused on enhancing the quality of pharmacy procurement systems through technological intervention[16]. The methodology integrates the Pareto Method (80/20 rule) for strategic data analysis with the Prototype Model for iterative system development. By utilizing historical sales data extracted from the Point-of-Sales (POS) system, this study aims to construct a web-based Decision Support System (DSS) that delivers accurate and profitable inventory recommendations, which are subsequently validated through comparative testing against manual procedures and the Rapid Miner data science tool.

2.1 Research Design

This study utilized a qualitative research approach focusing on the quality of the entity being researched, specifically the procurement system in a pharmacy business. The research design aimed to build a Decision Support System (DSS) application to provide accurate recommendations for pharmacists in decision-making[14]. The study focused on optimizing the Pareto Method to process sales recap data from the period of December 2023 at Apotek Setia Husada[10].

2.2 Research Framework

The research workflow began with coordination with the Pharmacist in Charge (APA) to define the scope and obtain permission for observation[1]. The framework involved . Throughout the process, the researcher continuously presented the application prototype to the APA to ensure the system met the user's requirements[16].

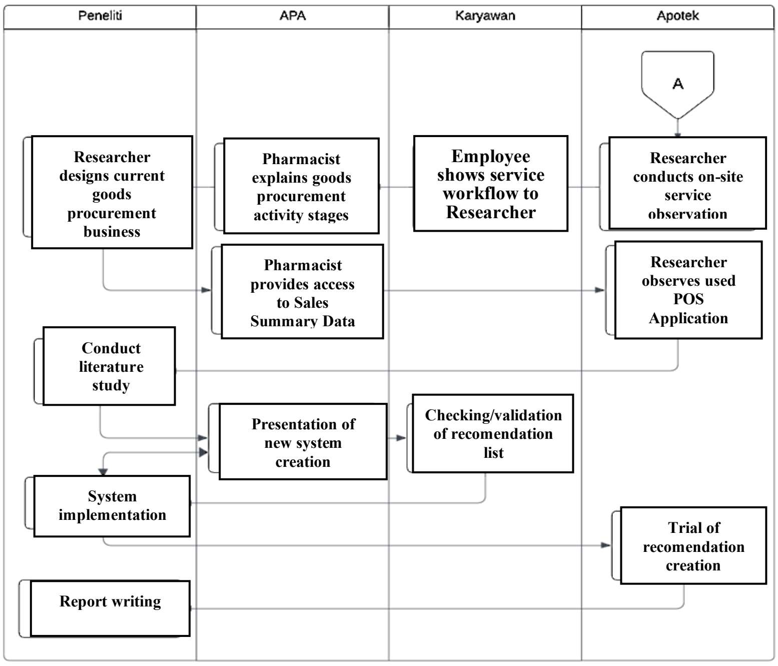

Figure 1. Research Work Process.

2.3 Data Collection

Data collection techniques employed in this study included:

1. Observation: Direct observation was conducted at Apotek Setia Husada to understand the existing stock management process, including the use of the Defecta Book and refusal logs[2].
2. Dataset Retrieval: The primary data used was the Sales Recap Report generated by the Point-Of-Sales (POS) application currently used by the pharmacy[5]. This data was extracted in .xlxs (Excel) format.
3. Literature Study: A review of relevant regulations, such as the Minister of Health Regulations and the Pharmacist Code of Ethics, was conducted to ensure the system complied with professional standards[1].

2.4 Data Processing Methods SIROP

The data processing in the proposed SIROP system begins with extracting the sales report from the POS application. The Excel file is then uploaded into the SIROP database. The system executes Structured Query Language (SQL) commands to read, calculate, and sort the data based on the Profit Margin variable derived from the buying price, selling price, and total sales volume[13], [17].

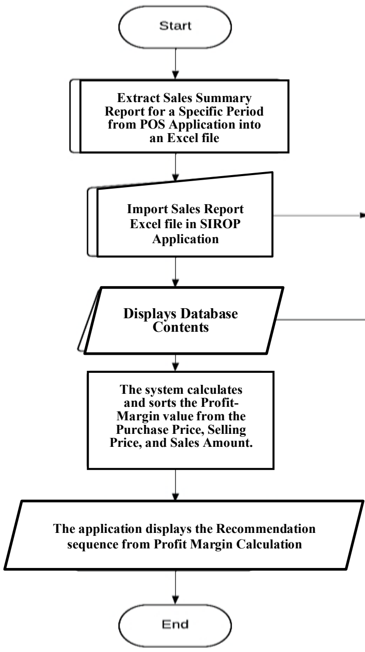

Figure 2. Data Analysis and Processing Flowchart

2.5 Pareto Method

The Pareto Principle, also known as the 80:20 rule, asserts that 80% of results are derived from 20% of causes. In the context of this study, the method was adapted to identify "Fast-Moving" items that contribute significantly to financial profit. The optimization process involves several classification variables: Product Embeddings, Sales Ability, Profit Margin, Customer Behavior, Fast Moving Product, Data Sorting, and Recommendation Product.

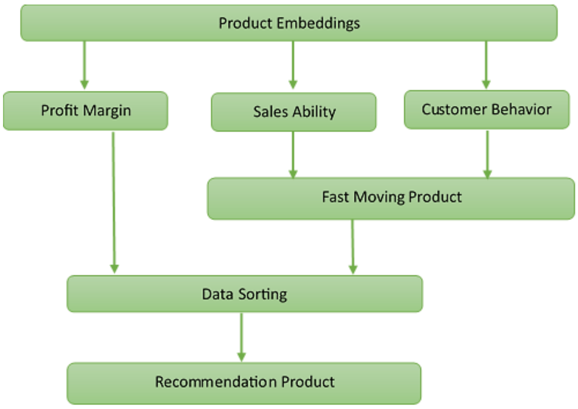

Figure 3. Data Processing Flow with Pareto Method.

As adapted from Pan Li et al. (2024), this flow processes data to classify items based on their influence on the core problem. Items with higher profit influence are sorted as top recommendations[18].

2.6 System Development Methods

The application was developed using the Prototype Model. This model was chosen to provide an early visualization of the working system to the pharmacist during the research process. The system is a web-based application built using the PHP programming language within the Codeigniter framework. It utilizes a local server (localhost) and SQL commands to manipulate the database content for recommendation generation[16]. The SIROP application workflow, as shown in Figure 40 below, was created to serve as a basis for developing a web-based application system.

2.7 Design Tools and Materials

The development and testing of the system utilized the following tools:

1. MySQL: Used as the Database Management System (DBMS).
2. Codeigniter: The framework used for designing the web application structure.
3. Sublime Text: The text editor used for writing PHP code.
4. Rapid Miner: A data science tool used for comparative analysis using K-Means and Pareto Rank algorithms.
5. Stopwatch: Used to measure the processing time during the testing phase.

2.4 System Testing

System testing was conducted in two stages:

1. Efficiency Testing: Comparing the time required to generate recommendations using the manual method versus the SIROP application.
2. Accuracy and Profitability Testing: Comparing the recommendation output of SIROP against the Rapid Miner application. Rapid Miner utilized the K-Means clustering algorithm and Pareto Rank operator to process the same dataset. The quality of the recommendations was validated by calculating the Gross Profit Margin (GPM) using the following equation, where SP is Selling Price and NBP is Net Buying Price [20] :

$$GPM = \frac{\sum_{1}^{n}(sp - npp)}{sp}\ x\ 100\% \qquad (1)$$

Where : *GPM = Gross Profit Magin, sp = sell price, npp = netto of pharmacy price*

This calculation determines the profitability of the recommended products from both systems.

3. RESULTS AND DISCUSSION

The implementation of the web-based Decision Support System (SIROP) was successfully executed using the Prototype Model. The system was designed to transform the pharmacy's procurement process from a manual, paper-based workflow into a digital, data-driven operation. The core functionality begins with the user uploading a sales recap file in Excel format. Once the data is ingested into the database, the system automatically processes the variables, specifically focusing on the "Total Sales" and "Profit" columns. Unlike the previous manual method where data was scattered across physical logbooks, the system consolidates this information to provide a unified view of inventory performance.

The primary mechanism of the system involves sorting and ranking inventory items based on the Pareto Principle. The algorithm calculates the "Profit Margin" by analyzing the spread between the buying price and the selling price, multiplied by the sales volume. This calculation ensures that the recommendations are not solely based on the number of items sold—which can be misleading if the margin is thin—but on the actual financial contribution of the product. By sorting data from the highest profit contribution to the lowest, the system identifies the vital 20% of items that generate the majority of the pharmacy's revenue.

To visualize these results, the system generates a Pareto Chart combining bar and line graphs. This visualization serves as a quality control tool, allowing pharmacists to quickly identify the "vital few" products versus the "trivial many". The analysis of the chart produced during the study revealed that among the sampled items, a small cluster of products significantly influenced the total profit. This graphical representation validates the relevance of the 80/20 rule in the pharmacy's sales data and provides immediate visual cues for procurement prioritization[19].

Operational analysis reveals a stark contrast between the new system and the legacy manual procedures. Previously, the procurement process relied on the "Defecta Book," "Refusal Book," and patient order notes, which were processed based on the pharmacist's subjective intuition. This manual approach was prone to human error, particularly in calculating order quantities, leading to risks of overstocking (expiration) or understocking (lost sales). The computerized system mitigates these risks by providing objective recommendations based on historical sales data, thereby removing the guesswork from inventory planning.

It is important to note that the implementation of this computerized SPK does not replace the professional role of the pharmacist. Instead, it serves as a strategic tool that enhances decision-making capabilities. By automating the complex calculations of profit margins and sales velocity, the system frees the pharmacist to focus on clinical services and final verification of orders. The results indicate that technology integration not only improves operational efficiency but also ensures that procurement decisions are accountable and transparent.

In addition to comparing with manual techniques, the testing phase of this research also compared the recommendation-making results between two applications: SIROP and Rapid Miner [15]. As shown in Figure 7, several steps in using SIROP and Rapid Miner are similar. However, processing with Rapid Miner requires data type configuration before the program can produce results, as shown in Figure 8 when the process design is executed.

3.1 Recommendation Accuracy Comparison

To ensure the reliability of the recommendations generated by the developed system, a validation process was conducted by comparing the output of the SIROP application against Rapid Miner, a widely recognized data science tool used for data mining and analytics. Both systems were subjected to the exact same dataset derived from the pharmacy's sales recap to ensure a fair "apple-to-apple" comparison. In Rapid Miner, the data processing utilized the K-Means clustering algorithm combined with the Pareto Rank operator to sort and classify the products based on their performance metrics[15].

The validation results, as presented in Table 1, display the top 10 recommended items generated by both applications. The comparison reveals a significant intersection in the "vital few" products identified by both systems, although the exact ranking order differs slightly due to the different algorithmic approaches (Direct Profit Sorting in SIROP vs. Clustering in Rapid Miner). For instance, items like "Dramamine Tab" appeared as the top recommendation in both lists, while other high-performing items like "Wiros Tab" and "Amlodipin" were present in both top-10 lists but at different ranks. This similarity in identifying key products confirms that the logic implemented in the SIROP web application is statistically valid and capable of producing industry-standard recommendations.

Table 1. Comparison Between Recommendations from the SIROP Application and Recommendations from the Rapid-Miner Application [15]

No.	Recommendations for Drug Procurement	
	SIROP	RAPIDMINER
1	Dramamine Tab	Dramamine Tab
2	Wiros Tab	Molacort 0.75 @200
3	Amlodipin 10 MG HJ ‘100	Wiros Tab
4	Piroxicam 20 MG Tab	GP Care Pink Test
5	RL OTSU	Amlodipin 10 MG HJ ‘100
6	Microgynon LIBI@10	Piroxicam 20 MG Tab
7	Andalan Tab @30 Kotak	Cataflam Tab 50 MG
8	GP Care Pink Test	Andalan Tab @30 Kotak
9	Molacort 0.75 @200	RL OTSU
10	NACL 0,9% 500 ML OTSU	Paracetamol Tab PIM/MERSI

3.2 Efficiency Analysis: Manual vs. System

A critical objective of this research was to measure the efficiency gains provided by the computerized system compared to the traditional manual method. The manual workflow at Apotek Setia Husada involves a laborious process: the pharmacist must physically check the "Defecta Book," cross-reference with the "Refusal Book," examine stock cards for sales history, and manually calculate the required order quantity for each specific item. This process is not only physically demanding but also highly susceptible to human error.

To quantify this, a time-motion study was conducted using a stopwatch. The results, detailed in Table 2, show a stark contrast. The manual process takes approximately 06 minutes and 20 seconds to process just one type of item. This duration includes 10 seconds for preparing notes, 1 minute for checking physical stock, 5 minutes for calculating sales from stock cards, and 10 seconds for recording the need.

Table 2. Comparison of Recommendation Generation Time Between the SIROP Application and Manual Methods

No	Stages of Recommendation Development			
	Manual Method	Time Range	Aplikasi SIROP	Time Range
1	Preparing Order Notes	00 : 00 : 10	Extract Sales Recap Reports from the POS application for a Specific Period	00 : 03 : 00
2	Checking the remaining stock of 1 type of item in the storage warehouse	00 : 01 : 00	Upload sales recap files to the SIROP Web Application	00 : 00 : 10
3	Calculating the sales amount of 1 Type of Goods from the Stock Card	00 : 05 : 00	Press the Button for Recommendations	00 : 00 : 05
4	Recording the requirements for 1 type of item	00 : 00 : 10	-	-
	Total	00 : 06 : 20	Total	00 : 03 : 15

In contrast, the SIROP application drastically reduces this time. As shown in Table 2, the entire process—from extracting the report (3 minutes), uploading the file (10 seconds), to generating the recommendation list (5 seconds)—takes a total of only 03 minutes and 15 seconds. Crucially, this 3-minute duration for the system generates recommendations for multiple items simultaneously, whereas the manual method's 6-minute duration applies to only single item. Figure 6 illustrates the scalability issue of the manual method; processing 10 items manually would take over an hour (approx. 1 hour 3 minutes), whereas the system maintains its rapid processing time regardless of the item count.

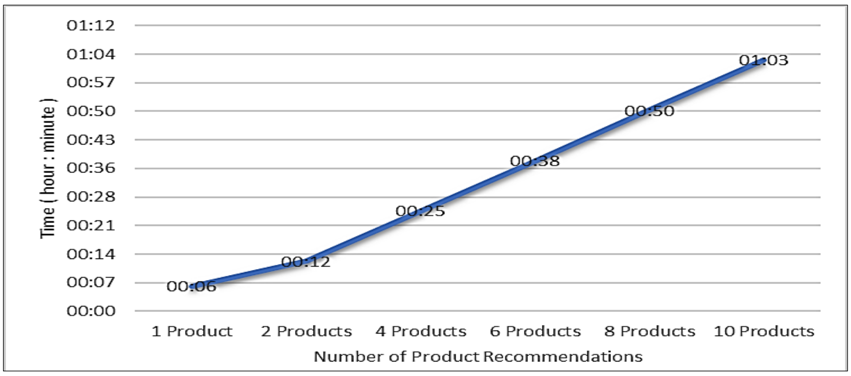

Figure 4. Time estimation for manual recommendation generation

3.3 Computational Efficiency: SIROP vs. Rapid Miner Result [15]

Beyond the manual comparison, the study also evaluated the computational efficiency of the custom-built SIROP application against the generic Rapid Miner [15]. While both are digital solutions, their workflows differ significantly. The Rapid Miner results in [15] researcher, being a general-purpose data science tool, requires pre-processing steps that add to the total execution time. Users must manually define data types for each column (e.g., integer, polynomial) after importing the Excel file before the algorithms can be executed. As shown in Figure 7, several stages between the use of SIROP and Rapid Miner have some similarities.

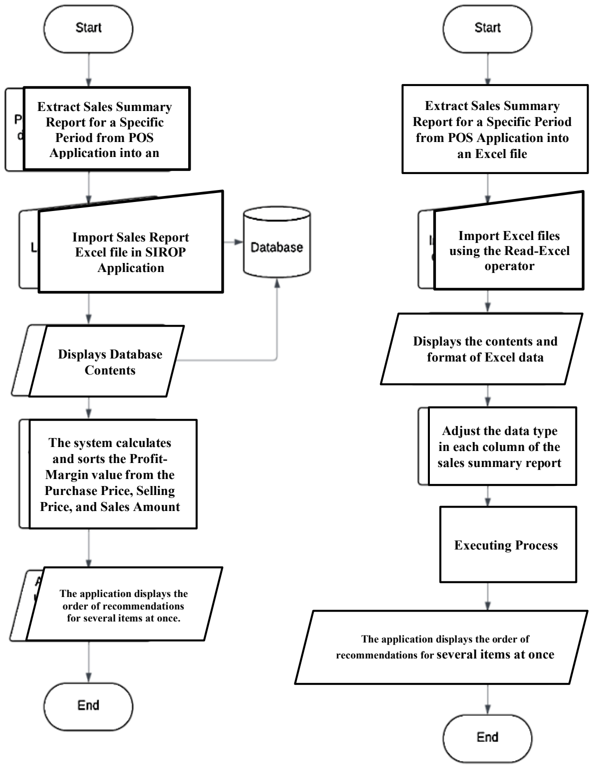

Figure 5. System Workflow Comparison: (a) SIROP (beside left). (b) Rapid Miner [15] (beside right).

Then Table 3 provides a breakdown of these processing times and Figure 8 shows the output complexity of Rapid Miner [15]. The SIROP application completed the task in 03 minutes and 15 seconds, while Rapid Miner required 04 minutes and 15 seconds. The additional minute in Rapid Miner is primarily consumed by the "Set Data Type" configuration step.

Table 3. Comparison of Recommendation Generation Time Between SIROP and Rapid Miner Result
Source : E. Widodo, A. T. Sasongko, and A. Z. Kamalia

No	Stages of Recommendation Development			
	SIROP	**Time Range**	**RapidMiner**	**Time Range**
1	Extract Sales Recap Reports from the POS application for a Specific Period	00 : 03 : 00	Extract Sales Recap Reports from the POS application for a Specific Period	00 : 03 : 00
2	Upload sales recap files to the SIROP Web Application	00 : 00 : 10	Upload sales recap files to the Read-Excel feature	00 : 00 : 10
3	Press the Button for Recommendations	00 : 00 : 05	Set the Data Type for each Column in the Imported Sales Recap Table	00 : 01 : 00
4	-	-	Process execution in RapidMiner	00 : 00 : 05
	Total	**00 : 03 : 15**	**Total**	**00 : 04 : 15**

3.4 Profitability Analysis (Gross Profit Margin)

The ultimate measure of the system's success is its ability to improve the pharmacy's financial performance. To evaluate this, the study calculated the Gross Profit Margin (GPM) for the top 10 recommended items from both systems. This metric determines how efficiently the pharmacy generates profit from its inventory investment[17]. Table 4 details the financial projection for the SIROP recommendations.

Table 4. Calculation of Investment Amount and % Profit Recommendation SIROP

Medication Recommendations	Total Sales	GPM	Investment	Profit
Dramamine Tab	221	35%	432.718	230.282
Wiros Tab	170	34%	394.910	200.090
Amlodipin 10 MG HJ ‘100	49	46%	225.400	191.100
Piroxicam 20 MG Tab	88	59%	125.048	182.952
RL OTSU	80	19%	679.840	160.160
Microgynon LIBI@10	58	12%	1.100.434	146.566
Andalan Tab @30 Kotak	85	10%	1.180.310	137.190
GP Care Pink Test	133	50%	133.000	133.000
Molacort 0.75 @200	189	33%	251.748	126.252
NACL 0,9% 500 ML OTSU	52	23%	398.996	121.004
Total			**4.922.404**	**1.628.596**

The top 10 items suggested by SIROP require a total investment of IDR 4,922,404 and are projected to yield a profit of IDR 1,628,596. The calculated average GPM for these items is 32.1%. In comparison, Table 5 shows the financial projection for Rapid Miner's recommendations.

Table 5. Calculation of Investment Amount and % Profit Recommendation by RapidMiner
Source : E. Widodo, A. T. Sasongko, and A. Z. Kamalia

No	Medication Recommendations	Total Sales	GPM	Investment	Profit
1	Dramamine Tab	221	35%	432.718	230.282
2	Molacort 0.75 @200	189	35%	370.062	196.938
3	Wiros Tab	170	23%	1.304.410	395.590
4	GP Care Pink Test	133	35%	260.414	138.586
5	Amlodipin 10 MG HJ ‘100	49	46%	225.400	191.100
6	Piroxicam 20 MG Tab	88	35%	172.304	91.696
7	Cataflam Tab 50 MG	120	13%	782.160	117.840
8	Andalan Tab @30 Kotak	85	10%	1.180.310	137.190
9	RL OTSU	80	19%	679.840	160.160
10	Paracetamol Tab PIM/MERSI	108	35%	211.464	112.536
	Total			**5.619.082**	**1.771.918**

While the total projected profit is slightly higher (IDR 1,771,918), the investment required is also significantly higher (IDR 5,619,082). Consequently, the average GPM for the Rapid Miner list is only 28.6%. As visualized in Figure 9, the SIROP application demonstrates superior efficiency.

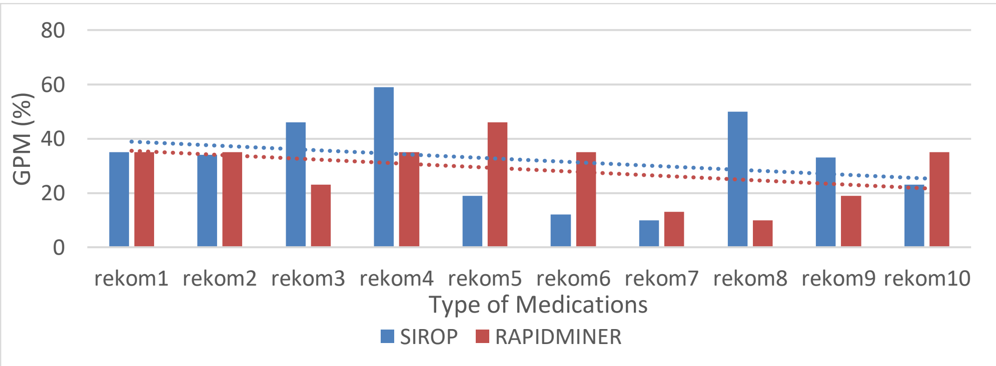

Figure 6. Comparison of Average GPM Percentage: SIROP vs. Rapid Miner.
Source : E. Widodo, A. T. Sasongko, and A. Z. Kamalia

It identifies products that provide a higher return on investment (32.1% vs 28.6%), which is crucial for maximizing the pharmacy's operational sustainability. This confirms that the specific Pareto optimization logic embedded in SIROP is better aligned with the pharmacy's profitability goals than the generic clustering approach. The data processing stage with Rapid Miner [15] requires prior data type configuration, which increases the time required. Another advantage is that the estimated profit calculation results are higher using SIROP application recommendations than using Rapid Miner's recommended product data.

3.5 Impact on Pharmacy Operations and Pharmacist Role

The implementation of SIROP brings a significant qualitative shift in the pharmacy's operational workflow. In the manual system, the pharmacist's time was heavily consumed by clerical tasks—checking physical stock logs and calculating needs manually. This repetitive administrative burden often distracted from the core responsibility of pharmaceutical care.

The computerized system automates these clerical tasks, effectively minimizing the risk of human error in calculation and recording. By shifting the computational load to the system, the pharmacist's role transforms from a technical administrator to a strategic decision-maker. As noted in the study, the use of this DSS does not undermine or displace the pharmacist's position; rather, it empowers them to focus on verifying the logic of orders and ensuring patient-oriented service. Furthermore, the system enhances transparency and accountability in procurement, as every recommendation is based on traceable data rather than subjective estimation.

3.6 System Limitations

While the system demonstrates significant advantages, this study identifies certain limitations that provide opportunities for future development. Firstly, the current dataset used for Pareto analysis is limited to the sales recap of December 2023. While sufficient for prototyping, a longer historical dataset would yield more robust seasonal trend analysis. Secondly, for the purpose of rapid access during the research trial, certain security features like complex login/logout procedures were temporarily simplified at the user's request to accelerate the workflow. Future iterations of the system should address these by integrating multi-period data analysis and enhancing security protocols without compromising access speed.

4. CONCLUSION

The research concludes that the implementation of the web-based Decision Support System (SIROP) significantly optimizes pharmacy procurement processes by automating the Pareto method, thereby replacing inefficient manual workflows without undermining the pharmacist's professional role. The system demonstrated superior performance in both efficiency and profitability, reducing the processing time for recommendation generation to 3 minutes 15 seconds—compared to over 6 minutes for manual methods—and achieving a higher Gross Profit Margin (GPM) of 32.1% against the 28.6% yielded by the Rapid Miner result [15]. By focusing on high-impact inventory items, the system minimizes human error and maximizes financial returns, proving that specialized, domain-specific applications can outperform general data mining algorithms in practical healthcare settings., The frameworks are highly applicable to healthcare inventory management while the document uses education as its primary example is Operational Efficiency and Error Reduction.

Operational Efficiency and Error Reduction : In education, IS automates scheduling and resource allocation to minimize errors. In Healthcare Inventory, this methodology applies to automated Stock Tracking, using IS to automate the tracking of surgical supplies and medication, reducing manual audit errors. Real-time Visibility, providing real-time access to stock levels of critical items like oxygen or vaccines.Future research should focus on expanding the system architecture to integrate directly with Point-of-Sales (POS) units for real-time data synchronization and predictive analytics.

REFERENCES

[1] K. K. R. Indonesia, "Peraturan Menteri Kesehatan Republik Indonesia Nomor 73 Tahun 2016." 2016.

[2] N. M. I. F. P. Dewi and I. M. A. G. Wirasuta, "Studi Perencanaan Pengadaan Sediaan Farmasi Di Apotek X Berdasarkan Peraturan Menteri Kesehatan Nomor 73 Tahun 2016," *Indonesian Journal of Legal and Forensic Sciences*, vol. 11, p. 1, 2021.

[3] A. D. P. Utami, M. Shoaliha, and F. Amirulah, "Gambaran Tingkat Kepuasan Pasien Terhadap Pelayanan Kefarmasian di Apotek Sembuh Kota Bekasi," *Jurnal Ilmiah Pharmacy*, vol. 11, p. 101, 2024.

[4] H. S. Salam and W. E. Rusmana, "Analisis Efisiensi Pengelolaan Obat Berdasarkan Metode Pareto/ABC Di Apotek Keluarga 8 Antapani Bandung," *Sosains*, p. 1211, 2021.

[5] A. F. Syuhada and B. E. Rukaya, "Gambaran Penjualan Dan Investasi Obat Over-The-Counter Apotek 'X' Kelurahan Karang Anyar Kota Tarakan Menggunakan Analisis ABC Tahun 2022," *Jurnal Borneo*, vol. 4, no. 2, pp. 47-54, 2024.

[6] M. M. Fathoni and al, "Pelayanan Kefarmasian di Beberapa Apotek di Indonesia Pada Era Pandemi Covid-19," *Jurnal Farmasi Komunitas*, vol. 8, p. 45, 2021.

[7] R. Arif and A. Gunawan, "Diagram Pareto dan Diagram Fishbone: Penyebab yang mempengaruhi keterlambatan pengadaan barang di Perusahaan Industri Petrochemicals Cilegon Periode 2020-2022," *Jurnal Riset Bisnis Dan Manajemen Tirtayasa*, vol. 7, pp. 1-10, 2023.

[8] P. Polak, M. Pristavka, and K. Kollarova, "Evaluating The Effectiveness Of Production Process Using Pareto Analysis," *Acta Technologica Agriculturae*, p. 18, 2015.

[9] A. Sabri, *Living The 80/20 Way by Richard Koch*. Jakarta: PT Gramedia, 2023.

[10] Sunarto and H. S. WN, *Buku Saku Analisis Pareto*. Surabaya: Prodi Kebidanan Magetan - Poltekkes Kemenkes Surabaya, 2020.

[11] N. Ayesya, “Analisis Pareto Dalam Perencanaan Produk Di Apotek,” *PT. Apotek Digital Indonesia*, Jul. 2022.

[12] N. F. Novianti and R. Emelia, “Analisis Pareto Obat Antidiabetes Sebagai Dasar Keputusan Pembelian Bagian Pengadaan Obat Di Apotek Kimia Farma 167 Cimahi,” *Sosains*, vol. 2, pp. 182-192, 2022.

[13] Lasriana and A. Gunaryati, “Sistem Informasi Berbasis Web Menggunakan Algoritma Squential Search dan Selection Sort,” *JIPI*, vol. 07, p. 392, 2022.

[14] S. R. WIcaksono, E. S. Krisnadiva, and A. B. Yulliermawan, “Sistem Pendukung Keputusan Pengadaan Perangkat Multimedia Kodam IV/DIP Semarang Dengan Metode Simple Additive Weighting (SAW),” *Jurnal Ilmiah Manajemen, Bisnis dan Kewirausahaan*, vol. 3, p. 204, 2023.

[15] E. Widodo, A. T. Sasongko, and A. Z. Kamalia, “Klasifikasi Barang Paling Laku (Pareto) Indomaret Untung Suropati 35 (T3M1) Menggunakan Rapidminer Dengan Metode Naive Bayes,” *SIGMA*, vol. 13, pp. 231-234, 2022.

[16] W. Kom, A. Pohan, and A. Safrudin, “Implementasi Metode Agile Development Dalam Perancangan Sistem Informasi Pemesanan Menu Pada Restoran,” in *SINTA*, 2022, p. 106,.

[17] C. E. N. Marita and Z. B. Ni’am, “Pengaruh Current Ratio Dan Gross Profit Magin Terhadap Pertumbuhan Laba Pada Perusahaan Food And Beverage,” *Sinta*, vol. 6, p. 1, 2023.

[18] P. Li and A. Tuzhilin, “Deep Pareto Reinforcement Learning for Multi-Objective Recommender System.” 2024.

[19] M. Alkiayat, “A Practical Guide to Creating a Pareto Chart as a Quality Improvement Tool,” *JQSH*, vol. 4, no. 3, pp. 83-84, 2021.

[20] A. Mokrini and T. Aouam. "A Decision-Support Tool For Policy Makers In Healthcare Supply Chains To Balance Between Perceived Risk In Logistics Outsourcing And Cost-Efficiency." *Expert Syst. Appl.*, 201 (2022): 116999. https://doi.org/10.1016/j.eswa.2022.116999.

[22] H. Smedberg and S. Bandaru. "Interactive Knowledge Discovery and Knowledge Visualization For Decision Support in Multi-Objective Optimization." *Eur. J. Oper. Res.*, 306: 1311-1329. 2022. https://doi.org/10.1016/j.ejor.2022.09.008.

[23] C. Franco and E. A. -Lizarazo. "Optimization Under Uncertainty Of The Pharmaceutical Supply Chain In Hospitals." *Computers & Chemical Engineering*, 135:106689. 2020. https://doi.org/10.1016/j.compchemeng.2019.106689.

[24] J. Corny, A. Rajkumar, O. Martin, X. Dode, J. Lajonchère, O. Billuart, Y. Bézie and A. Buronfosse. "A Machine Learning–Based Clinical Decision Support System To Identify Prescriptions With A High Risk of Medication Error." *Journal of the American Medical Informatics Association : JAMIA*, 27:1688-1694. 2020. https://doi.org/10.1093/jamia/ocaa154.

[25] V. M. M. Siregar, S. Sonang and E. Damanik. "Sistem Pendukung Keputusan Penentuan Pelanggan Terbaik Menggunakan Metode Weighted Product." *Jurnal Teknik Informasi dan Komputer (Tekinkom)* 2021. https://doi.org/10.37600/tekinkom.v4i2.392.

[26] C. Ash, C. Diallo, U. Venkatadri and P. Vanberkel. "Distributionally Robust Optimization Of A Canadian Healthcare Supply Chain To Enhance Resilience During The COVID-19 Pandemic." *Computers & Industrial Engineering*, 168: 108051 - 108051. 2022. https://doi.org/10.1016/j.cie.2022.108051.

[27] A. Pentrakan, C. -C. Yang and W. Wong. "How Well Does A Sequential Minimal Optimization Model Perform In Predicting Medicine Prices For Procurement System?." *International Journal of Environmental Research and Public Health*, 18, 2021. https://doi.org/10.3390/ijerph18115523.

[28] K. Qiu, J. Chen, S. Ashraf and T. Shahid. "Strategic Decision Support System With Probabilistic Linguistic Term Sets: Extended CRADIS Approach for Supply Chain Risk Management in Sports Industry." *IEEE Access*, 13: 32853-32862. 2025. https://doi.org/10.1109/access.2024.3416391.

[29] P. S. Dosantos, A. Bouchet, I. M. Collado and S. Montes. "OPSBC: A Method To Sort Pareto-Optimal Sets Of Solutions In Multi-Objective Problems." *Expert Syst. Appl.*, 250:123803. 2024. https://doi.org/10.1016/j.eswa.2024.123803.

[30] F. P. Dewanti, S. Setiyowati and S. Harjanto. "Prediksi Persediaan Obat Untuk Proses Penjualan Menggunakan Metode Decision Tree Pada Apotek." *Jurnal Teknologi Informasi dan Komunikasi (TIKomSiN)* 2022. https://doi.org/10.30646/tikomsin.v10i1.604.

[31] C. Bogaerts, N. Schoenmaekers, M. Haems, M. Storme and H. De Loof. "A quality Improvement Study Of The Implementation And Initial Results Of A Pragmatic Clinical Decision Support System In The Community Pharmacy Setting." *International Journal of Clinical Pharmacy*, 46:141-149. 2023. https://doi.org/10.1007/s11096-023-01648-z.

[32] M. Puruhito, & A. Falani. "Decision Support System For Developing Application For Pharmaceutical Supplies Using The MMSL And Pareto Law Methods." , 4, 12-22. 2021. https://doi.org/10.29138/ijeeit.v4i1.1329.

[33] M. Fernández, P. Chanfreut, I. Jurado, and J. Maestre. A Data-Based Model Predictive Decision Support System for Inventory Management in Hospitals. *IEEE Journal of Biomedical and Health Informatics*, 25, 2227-2236. 2020. https://doi.org/10.1109/jbhi.2020.3039692.