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Integrating Moving Average Based Procurement Recommendations into a Web Based Pharmacy Order Form

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ABSTRACT – *Manual medicine procurement in pharmacies risks both stockouts and overstocking. This study aims to design and implement a medicine ordering module that integrates procurement recommendations based on moving average forecasting into the order form of a web-based pharmacy information system. The module, built with PHP and MySQL, computes the 30-day average daily sales, the estimated days until stockout, a risk classification, and a recommended quantity that raises stock to a target level of twice the predicted demand, and then fills the order form automatically. The evaluation used the database of Apotek Madani BS, which contains 5,564 sales transactions and 35 purchase orders. Of the 269 medicines sold in the last 30 days, 20 were critical, 3 were warning, and 246 were safe; 101 medicines were recommended for ordering, 78 of them with safe status. The module's output matched that of an independent implementation of the same algorithm, which confirms consistent implementation but not the operational validity of the underlying procurement policy, and 67.4% of historical order lines were preceded by sales in the previous 30 days. The design removes the manual copying of recommendations and can be adapted to other PHP- and MySQL-based pharmacy information systems; the recommended quantities have not yet been tested against future demand, and the module does not yet consider supplier lead time or seasonal patterns.*

Keywords – *Inventory management; Moving average; Pharmacy information system*

Mengintegrasikan Rekomendasi Pengadaan Berbasis Rata-rata Bergerak (Moving Average) ke dalam Formulir Pemesanan Farmasi Berbasis Web

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1. INTRODUCTION

A pharmacy is a pharmaceutical service facility that must always keep medicines available while preventing excess inventory. Stockouts reduce service quality and eliminate sales opportunities, whereas overstocking ties up working capital and increases the risk of expired medicines [1], [2], [3], [4]. In small pharmacies, procurement decisions often still rely on manual observation and conventional record keeping, so the results are difficult to keep consistent [5]. A survey of retail pharmacies in Ogun, Nigeria, found that medicine demand forecasting still relied mostly on qualitative and naive methods, whose accuracy is considerably lower [6]. In community health centers (*puskesmas*) that have not calculated safety stock and reorder points, stockouts also remain common [7].

Pharmacy information systems generally already record sales and stock, but these data often remain mere transaction archives. Previous studies have built reorder recommendation systems and combined demand forecasting with order-quantity models (Section 2), and they concentrate on methods for determining when and how much to order. Wulandari and Mulyati [8] do provide an automatic ordering feature based on a recommendation table; however, in the articles reviewed, how calculation results are transferred to the order form, including the handling of various packaging units and the protection of unsaved input, is not discussed.

Table 1 (Section 2) summarizes how this study differs from the earlier work. First, the object of study is not another forecasting or order-quantity method but the path from a recommendation to a completed order document, including selection by priority, conversion of packaging units to PCS, and protection of unsaved input. Second, the recommendation policy is split into a prioritization layer (risk status) and a replenishment layer (target stock level), and the relationship between the two is analyzed explicitly rather than assumed. Third, the evaluation uses the operational data of a working pharmacy and states what each test can and cannot establish.

Similar conditions are found in the information system of Apotek Madani BS, which serves as the case study. The system has recorded 5,564 sales transactions since December 2025 and 35 purchase orders in 2026. Each order contains an average of 26.6 items, with a maximum of 77, and 43.0% of item lines are ordered in a large packaging unit (box, carton, strip, or pack) that must be converted to the smallest unit to calculate the order value. Under such a workload, manually copying recommended quantities from a report into the order form is slow and error-prone. In a clinical data repository, manual entry produced transcription errors in 2.8% of fields when compared with electronically imported data [9].

Earlier research on the same system evaluated the usability of a pharmacy information system that contains a medicine demand forecasting module based on moving average [10]. This article does not evaluate the accuracy of that forecasting. Its focus is integration engineering, that is, how forecasting results are converted into quantity recommendations and entered directly into the order form.

The objectives of this study are to design and implement a medicine ordering module that integrates moving average-based recommendations into the procurement form, to verify the correctness of the recommendation calculations on the pharmacy's operational data, and to analyze the relationship between order history and sales patterns in order to assess the relevance of the recommendations. The contributions of this study are (i) a workflow and algorithm design for transferring recommendations into the order form that can be applied to other pharmacy information systems based on PHP and MySQL; (ii) an explicit analysis of how the risk classification relates to the purchase trigger; and (iii) an evaluation whose claims are bounded, separating the consistency of the calculation from the operational validity of the policy.

2. LITERATURE REVIEW

Procurement Recommendation Systems for Pharmacies

Several studies have built reorder recommendation systems based on reorder point and safety stock [8] and combined weighted moving average forecasting with the Economic Order Quantity (EOQ) in a pharmacy information system [11]. Similar approaches have been reported in a web-based information system using PHP and MySQL with EOQ and reorder point (ROP) for pharmaceutical inventory planning and control [12], in an ordering prediction system for

a pharmacy using EOQ and ROP [13], and in applications that forecast medicine sales and inventory using the single moving average [14] and the weighted moving average [15]. These studies focus on methods for determining the timing and quantity of orders.

Moving Average Forecasting and Safety Stock

A simple moving average is a reasonable choice for pharmacies with a short sales history because it requires only one parameter, the window length, and is easy to explain to staff. A study at another pharmacy reported that a single moving average with a four-week window reached an accuracy of about 86% for the ten best-selling medicines [16]. A recent review maps classical statistical models to stable demand patterns and machine learning to demand surges [17]. Safety stock to anticipate lead time and demand uncertainty is common in pharmaceutical inventory control, for example through the calculation of safety stock and reorder points [7], and lead-time uncertainty can be handled with a dynamic, forecast-based reorder point policy that has been tested on pharmaceutical industry demand data [18].

Positioning of This Study

Table 1 positions the present work against the related studies discussed above. Most of them address what to order and when: reorder points and safety stock [8], weighted moving average with EOQ [11], EOQ and ROP in a web-based system [12], EOQ and ROP for order prediction [13], and sales forecasting with the single [14] or weighted moving average [15]. Romadhon and Wardoyo [19] combine ABC and VEN analysis with EOQ and ROP to present procurement recommendations to decision makers. The system of Wulandari and Mulyati [8] is the closest to the present work, because users can place an order from the recommendation table. In the articles reviewed, however, how recommended quantities reach the order form, including the conversion of packaging units and the protection of unsaved input, is not described. This is the gap that the present module addresses, and the evaluation in Section 3 is designed to claim no more than the data allow.

Table 1. Related studies and the position of this study

Study	Method	Main output
[8]	Reorder point, safety stock	Reorder recommendation table; automatic ordering from the table
[11]	WMA, EOQ	Demand forecast and order quantity in a stock control system
[12]	Consumption method, EOQ, ROP	Drug planning and inventory control; checked against Excel and black-box tests
[13]	EOQ, ROP	Order prediction and stock control
[14]	Single moving average	Drug sales prediction
[15]	WMA, single exponential smoothing	Method comparison for determining drug inventory
[19]	ABC, VEN, EOQ, ROP	Procurement recommendations for decision makers
This study	30-day moving average, order-up-to level	Recommendation entered into the order form with unit conversion and draft protection

WMA: weighted moving average. Method and output are summarized from the cited articles.

3. RESEARCH METHODS

Research Design

This study is a design and development study with a single case study of the information system of Apotek Madani BS. The stages comprise requirements analysis of the procurement workflow, design of the recommendation algorithm and user interface, implementation, and evaluation using operational data.

Place, Time, and Data

Operational data were taken from a backup of the Apotek Madani BS database dated 22 October 2026. Sales data cover 3 December 2025 to 22 October 2026, whereas orders have been recorded since January 2026. All records in the procurement-related tables were used without sampling (total sampling), as shown in Table 2. All sales transactions have the status completed, and the sales return table contains no data in the analyzed backup.

Table 2. Data used

Database table	Number of rows
penjualan (sales)	5,564
detail_penjualan (sales details)	8,386
obat (medicines; active: 519)	1,651
stok_obat (medicine stock)	1,682
pemesanan_obat (medicine orders)	35
pemesanan_obat_detail (order details)	930
suppliers	8

Implementation Environment

The module was implemented in PHP, which accesses MySQL through PDO. The interface uses Bootstrap and jQuery, with Select2 for medicine search and SweetAlert2 for confirmation dialogs. List pages are loaded through AJAX requests so that the form being filled is not lost when staff move between list pages.

Database Design

Orders use a header–detail structure, as shown in Table 3. The header table stores the order number, date, supplier, user, status, and signature, whereas the detail table stores the medicine, quantity, and order unit for each item, with a cascading-delete relationship to the header. Stock is stored per batch, so the stock of a medicine is obtained by summing the batches with the status available.

Table 3. Main attributes of the order tables

Table	Main attributes
pemesanan_obat	*id_pesanan, no_pesanan* (unique), *tanggal_pesan, id_supplier, catatan, signature, id_user, status*
pemesanan_obat_detail	*id, id_pesanan* (foreign key), *id_obat, jumlah, kategori* (unit)
stok_obat	*id_obat, batch_number, tanggal_kadaluarsa, jumlah_stok, status*

Table and attribute names are kept as in the (Indonesian-language) database.

Recommendation Algorithm

Recommendations are computed only for active medicines sold in the last 30 days (D > 0). The average daily sales r is calculated with Equation (1), and the 30-day demand prediction P with Equation (2). Because no additional safety factor is used, P is essentially equal to the total sales of the last 30 days. The estimated number of days until stockout H is calculated with Equation (3), where S is the available stock summed over all batches.

$$r = \frac{D}{30} \quad (1)$$

$$P = \lceil r \times 30 \rceil \quad (2)$$

$$H = \lfloor S / r \rfloor \quad (3)$$

A medicine's status is set to CRITICAL if H ≤ 7 days, WARNING if 7 < H ≤ 14 days, and SAFE if H > 14 days. The recommended quantity Q is the shortfall of the available stock S against a target stock level of twice the prediction, as in Equation (4); a positive Q therefore means that the stock is smaller than the 60-day demand. The status and the quantity serve different purposes, as explained in the design rationale below.

$$Q = max(0, 2P - S) \quad (4)$$

The order value V is calculated as the sum of the product of the purchase price per PCS and the number of PCS of each item. For the units *KOTAK* (box), *DUS* (carton), *STRIP*, and *PAK* (pack), staff enter the total number of PCS explicitly because package contents differ between products, whereas for PCS and *BOTOL* (bottle) the entered quantity is used directly.

Algorithm 1. Procurement recommendation

```
retrieve active medicines, D, S
for each medicine with D > 0:
    r = D/30; P = ceil(r × 30)
    H = floor(S/r)
    status = CRITICAL if H ≤ 7, WARNING if H ≤ 14, otherwise SAFE
    Q = max(0, 2P − S)
sort: CRITICAL, WARNING, SAFE
display; the add button inserts Q
```

Design Rationale of the Recommendation Policy

A simple moving average over the last 30 days was chosen for three reasons. First, the database holds only about ten months of sales, which is too short to estimate seasonal components or to fit and validate the parameters of more elaborate methods. Second, the moving average is a basic smoothing technique whose only parameter is the window length [20], so staff can reproduce and question a recommendation by hand. Third, it can be computed directly in the module's SQL query from the existing sales and stock tables. The 30-day window is a compromise: it is long enough to smooth day-to-day noise for medicines that sell only a few units per month (Section 4), yet short enough to follow changes in demand within a month, and a four-week window has been used in a comparable pharmacy study [16]. Methods designed for intermittent demand, such as Croston's method [21] and its bias-corrected variant [22] were not used because they need enough history to estimate both the size of demands and the intervals between them, and demand can be categorized by these two properties to choose among such methods [23] Neither the method nor the window is claimed to be optimal; both are parameters of the module.

The recommended quantity follows an order-up-to (base-stock) logic [24]: staff order the amount needed to bring stock back to a target level, here twice the 30-day prediction. The factor of two is a heuristic that doubles the planning horizon: one month of expected demand plus an equal buffer against supplier lead time and demand uncertainty. It is not derived from a

service-level target, because that would require supplier lead times and the demand variability of each medicine to set the safety stock, as in the reorder point approaches of [7] and [18]. Equation (4) also uses only the available stock on hand. Quantities that have been ordered but not yet received are not subtracted, whereas order-up-to systems normally work with the inventory position, that is, stock on hand plus stock on order [24]. Both simplifications are treated as limitations in Section 5.

The risk status and the purchase trigger answer different questions, as summarized in Table 4. The status ranks medicines by how soon the present stock runs out and sets the order in which staff see them. The purchase trigger is $Q > 0$, which is equivalent to $H < 60$ days. The two criteria are therefore nested rather than identical: it follows from Equations (2) to (4) that every medicine with $H \leq 14$ days has $Q > 0$, whereas a SAFE medicine receives a recommendation whenever its stock covers fewer than 60 days. The module keeps both layers on purpose. The priority filters "Only CRITICAL" and "CRITICAL + WARNING" let staff apply an urgency-based trigger of 7 or 14 days, whereas the full list applies the 60-day target. Section 4 reports how many medicines and how much quantity fall into each layer.

Table 4. Relationship between risk status and purchase trigger

Status	Condition	Q > 0	Role
CRITICAL	$H \leq 7$	Always	Order first
WARNING	$7 < H \leq 14$	Always	Order soon
SAFE	$14 < H < 60$	Yes	Refill to target level
SAFE	$H \geq 60$	No	No action

H: estimated days until stockout. Q: recommended quantity. $Q > 0$ is the purchase trigger.

Testing and Data Analysis

Testing consisted of three parts, each supporting a different and limited claim. First, calculation verification: the recommendation query was run on the database backup with a reference date of 22 October 2026, and its output was compared with an independent implementation in Python for the number of medicines per status, the number of recommended medicines, the total quantity, and the estimated value, using a comparison approach similar to the testing of another web-based pharmaceutical inventory planning system [12]. Both implementations follow the same specification (Equations (1) to (4) and Algorithm 1). Agreement therefore shows that the SQL query implements the specification without coding or data-handling errors; it does not show that the specification is a good procurement policy, that the forecasts are accurate, or that the recommended quantities improve stock availability. Second, black-box functional testing of the form's behavior, which shows that the form behaves as specified, not that staff find it more efficient. Third, descriptive analysis of the order history: each order item line was checked to determine whether the medicine was sold in the 30 days before the order date. The proportion of lines with sales was used as an indicator of the relevance of sales-based recommendations, not as a measure of accuracy, because the stock level on each order date was not recorded and the recommendations could not be replayed against staff decisions. Forecast accuracy, stockout frequency, and working time were outside the scope of this study (Section 5).

4. RESULTS

Module Workflow and Interface

The module workflow is shown in Figure 1. Sales and stock data are processed into a risk status and a recommended quantity, and staff then move items to the form with one click, by priority, or all at once. The form automatically fills in the medicine name, the PCS unit, the recommended quantity, and the purchase price, so that the total order value is calculated immediately.

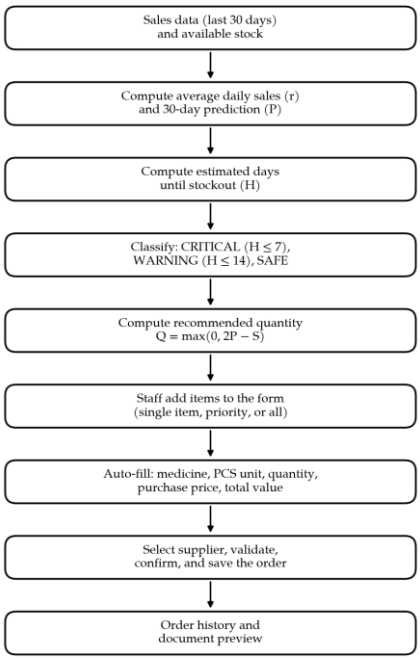


Figure 1. Workflow for integrating recommendations into the order form

The ordering page provides three sources of item lists: the 30-day prediction results, medicines with stock below the minimum, and medicines

that are out of stock. The prediction list provides an add-all-recommendations button and the priority filters "Only CRITICAL" and "CRITICAL + WARNING." The system rejects the addition of medicines that are already in the form and skips medicines with Q = 0 during bulk addition. The interface is shown in Figure 2.

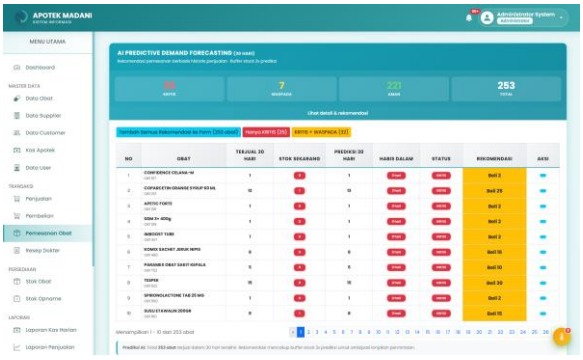


Figure 2. Interface of the medicine ordering page (Indonesian-language interface; KRITIS = critical, WASPADA = warning, AMAN = safe)

Form input is saved as a draft in the browser's local storage and restored if the page is reloaded within 24 hours; the draft is deleted after the order is saved or the form is reset. Orders are submitted through AJAX, recorded in the header and detail tables, and then appear in the order history, which contains the order number, date, supplier, and a document preview. In the header table, the medicine and quantity columns inherited from the legacy design contain zero in all 35 orders, whereas item details are stored in the detail table. The order unit is stored in the category column (*kategori*) of the detail table.

Calculation Verification Results

On the reference date of 22 October 2026, 269 of the 519 active medicines had been sold in the last 30 days. The results are summarized in Table 5. The number of medicines per status, the number of recommended medicines, the total quantity, and the estimated value from the module's query are identical to the results of the independent implementation. This identity shows that the query reproduces the specified calculation; it does not show that the recommended quantities match future demand or improve stock availability, which were not tested. The estimated value of all recommendations is IDR 12,776,685 based on the recorded purchase prices.

Table 5. Classification and recommendation results

Status	Medicines	Ordered	Q (PCS)
CRITICAL	20	20	207
WARNING	3	3	55
SAFE	246	78	1,055
Total	269	101	1,317

Ordered: number of medicines with Q > 0. Q: total recommended quantity.

Only 23 medicines (8.6%) have the status CRITICAL or WARNING, but 101 medicines (37.5%) receive a recommendation. The difference comes from 78 medicines with the status SAFE that still receive a recommendation because their inventory is less than the 60-day demand. These 78 medicines make up 77.2% of the recommended medicines and 1,055 of the 1,317 recommended PCS (80.1%), whereas CRITICAL and WARNING medicines account for the remaining 262 PCS (19.9%). The status thresholds (7 and 14 days) therefore differ from the purchase trigger (60 days), as designed in Section 3. In addition, of the 113 active medicines with no available stock, only 18 appear in the prediction list because they had sales in the last 30 days. The other medicines can be reached only through the out-of-stock list, which explains why the module provides three list sources.

Examples of CRITICAL medicines with zero or near-zero stock and high 30-day sales on the reference date are shown in Table 6. Because the stock is at most one unit, H is at most two days, and the recommended quantity follows the twice-the-prediction rule.

Table 6. Examples of CRITICAL medicines with zero or near-zero stock

Medicine	S	D	H	Q
Lodecon Forte	0	16	0	32
Coparcetin Orange Syrup 60 Ml	1	13	2	25
Imboost sachet	0	8	0	16
Komix sachet jeruk nipis	0	8	0	16
Komix sachet OBH	0	7	0	14
Candesartan 16 Mg	0	3	0	6

S: available stock. D: 30-day sales. H: days until stockout. Q: recommendation (PCS).

Demand per medicine is small and uneven. The average 30-day sales of the medicines on the prediction list is only about 8 units, the highest value is 350 units, and only one medicine sold 100 units or more.

Order History Analysis

The order history consists of 35 orders containing 930 item lines for 377 different medicines (Table 7). Orders are concentrated on one main supplier, which received 20 orders (57.1%), followed by a second supplier with 11 orders (31.4%).

Table 7. Summary of the order history

Indicator	Value
Number of orders	35
Item lines	930
Different medicines	377
Mean items per order	26.6
Median items per order	26
Range of items per order	1–77
Lines with sales in the preceding 30 days	627 (67.4%)

The unit distribution in Table 8 shows that 400 of the 930 lines (43.0%) use a large packaging unit that requires conversion to PCS. This finding supports the decision to design the total-PCS field as a mandatory input for these units.

Table 8. Distribution of order units

Unit	Lines	Percentage
PCS (pieces)	380	40.9%
KOTAK (box)	355	38.2%
BOTOL (bottle)	150	16.1%
STRIP	20	2.2%
PAK (pack)	13	1.4%
DUS (carton)	12	1.3%

In total, 627 of the 930 item lines (67.4%) were ordered for medicines sold in the 30 days before the order date, whereas 303 lines (32.6%) had no sales in that window. The monthly proportions are shown in Figure 3. April differs markedly: only 5 of 65 lines had prior sales. Examination of the data shows that 56 of those 65 lines refer to medicines that were registered in the medicine table only after the order date, coinciding with the addition of 1,205 medicines in April 2026, and 57 lines were first sold only after the order was made. This pattern is consistent with the ordering of new items or initial stock filling, rather than ordering based on previous sales.

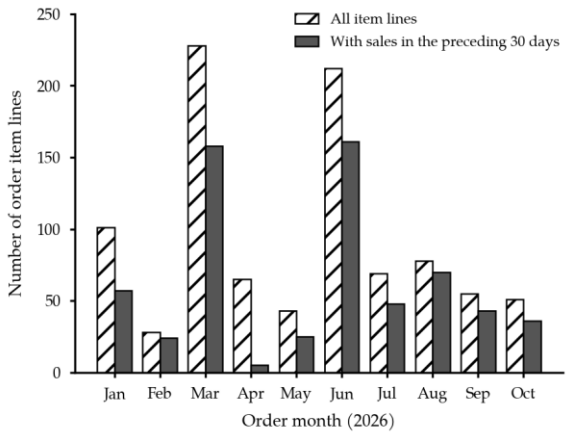


Figure 3. Order item lines per month and those preceded by sales

Functional Testing

The functional test scenarios were derived from the behavior of the form, as listed in Table 9. All scenarios produced behavior consistent with the expected results.

Table 9. Functional test scenarios

No	Scenario and expected result	Status
1	The add button on a single prediction row fills in the medicine name, the PCS unit, and the quantity according to the recommendation	Pass
2	Adding a medicine that is already in the form is rejected with a warning	Pass
3	The "Only CRITICAL" button adds only CRITICAL medicines with Q > 0	Pass
4	The add-all button skips medicines with Q = 0	Pass
5	The units *KOTAK*, *DUS*, *STRIP*, or *PAK* display a mandatory total-PCS field	Pass
6	The total order value equals the sum of purchase price multiplied by the PCS quantity	Pass
7	Reloading the page restores the draft input	Pass
8	Saving without selecting a supplier is rejected	Pass
9	Saving a valid order generates an order number, deletes the draft, and adds the order to the history	Pass

Scope of the Results

The results establish three things: the module's query reproduces the specified calculation on the operational data; the nine functional scenarios behaved as expected; and 627 of the 930 historical order lines (67.4%) were for medicines sold in the preceding 30 days. They do not establish that the recommended quantities are operationally optimal, that they match actual future demand, or that they improve stock availability, because the recommendations were not replayed against subsequent sales or stock levels and the effect on working time was not measured.

5. DISCUSSION

Comparison with Previous Research

Earlier systems built on reorder points [8], weighted moving average with EOQ [11], EOQ and ROP [12], [13], or single and weighted moving averages [14], [15] deliver demand figures or recommendation tables. The module in this study adds a direct path from those figures to a complete order document, with unit conversion and protection of input data, which is the gap identified in Section 1. By design, this path eliminates manual copying, although the

reduction in working time has not been measured in this study. This direction is consistent with a report that a drug supply chain information system in a hospital in China reduced the average annual inventory error from 0.425‰ to 0.025‰ [25], although that system differs in scope from a pharmacy order form.

The calculation check in this study is of the same kind as in Drug PC [12], whose EOQ and ROP results were reported to be consistent with Excel calculations. Both establish that a system computes what its specification says; neither is evidence of forecast accuracy or of better inventory outcomes. The analysis of historical orders adds a plausibility check on relevance, but not more than that.

Reported moving average accuracy also needs careful transfer. A single moving average with a four-week window reached an accuracy of about 86% for the ten best-selling medicines of another pharmacy [16], whereas in the present data the medicines on the prediction list sold only about 8 units in 30 days on average and only one sold 100 units or more. Results for fast-moving items should therefore not be assumed to hold for the long tail of slow-moving medicines.

Interpretation of the Findings

The identity between the module's output and the independent implementation confirms that the SQL query implements the specification correctly. Because both follow the same algorithm, it cannot reveal whether the algorithm itself, with its 30-day window, factor of two, and 7- and 14-day thresholds, is a good procurement policy. That question needs outcome data, such as stockout days and expired stock, which the current database cannot provide.

A simple moving average is a reasonable choice for a pharmacy with a short sales history, as argued in Section 3. The analyzed database, however, contains only about ten months of sales, so annual seasonal patterns cannot yet be modeled. Consequently, the 30-day prediction is sensitive to short-term spikes. Because demand per medicine is small and uneven (Section 4), a single large transaction can shift the average, and a buffer of twice the prediction can multiply such a spike into the order quantity.

The gap between the risk status and the purchase trigger is an important design finding. The 60-day target produces recommendations for 78 medicines that are still safe according to the 14-day threshold, and these medicines account for about 80% of the recommended quantity. This is reasonable if supplier lead times are long, but it adds to the capital burden if they are not. The order history points to the second possibility: 35 orders were placed between 30 January and 14 October 2026, roughly one order every 7 to 8 days on average, so the effective review period may be much shorter than the 30 days implied by the target. Lead time and safety stock commonly serve as the basis for determining reorder points [7], and lead-time uncertainty can be handled with a dynamic, forecast-based reorder point policy [18]. However, stock buffering is a reactive strategy that has been reported to be less effective in the long term unless it is accompanied by proactive measures such as stock assessment and efficient procurement [26]. An estimated recommendation value of more than IDR 12 million on a single reference date indicates the need for a buffer parameter that can be set per supplier or per medicine group. Grouping medicines by consumption value and criticality, for example through ABC–VEN analysis, is a common approach to determining control priorities; its application has been associated with a 35%–60% reduction in inventory cost [27] and with reduced inventory waste [1].

The 67.4% of order lines preceded by sales indicates that most historical procurement is in line with recent demand, but this figure is not a measure of recommendation accuracy. The remaining third of the lines may be new items, slow-moving items, or legitimate stock preparation; the pattern in April (Figure 3) points to initial stock filling. A stronger measurement requires recording historical stock per date so that recommendations can be retested against staff decisions. The quality and timeliness of data recording have also been reported as major challenges in medicine demand forecasting [28].

The low and intermittent demand shown in Table 6 has two consequences. For low-selling medicines, a buffer of twice the prediction yields a small quantity that may fall below the supplier's package multiple, so staff may need to round up. For medicines that did not sell at all in 30 days but have zero stock, the module produces no recommendation; such cases are captured only by the out-of-stock list. Sales-based recommendations should therefore be regarded as a prioritization tool and not as a substitute for staff judgment. For intermittent demand, Croston-based methods have been compared with the simple moving average and single exponential smoothing, and a new method derived from them was reported to perform better on 3,000 automotive spare-parts series [29].

Implications

For pharmacy practice, the module turns recommendations that would otherwise stay in a report into entries in the order form. This targets a known error source: in a clinical data repository, manual entry produced transcription errors in 2.8% of fields [9].The effect on error rates and working time was not measured here, so the benefit remains a design expectation. The module is meant to prioritize and pre-fill, and the staff decision stays with the pharmacist.

For system design, the study offers a transferable pattern. This design can be applied to other pharmacy information systems that hold three basic datasets: sales by date, stock by batch, and purchase price. A pharmacy can adjust the sales window, status thresholds, and buffer factor without changing the form workflow. The draft-saving feature is also relevant for large orders, because the largest order in the data contains 77 items and its preparation can be interrupted by service work.

For research on pharmacy procurement systems, the study suggests two reporting practices: stating how a risk status relates to the purchase trigger, and reporting the verification of a calculation separately from the validation of the policy it implements. Without this separation, agreement between two implementations is easily read as evidence of operational benefit.

Limitations

This study has several limitations. First, the recommendation does not yet account for supplier lead time or for prices and discounts across suppliers, although lead time affects the determination of the reorder point [7], [18].Second, the recommended quantity is always in PCS, so staff still have to convert it to packaging units when ordering. Third, the sales query does not yet exclude canceled transactions or subtract returns; in this backup all transactions have the status completed and the return table is empty, so the results are unaffected, but this must be addressed before the module is used on data containing returns. Fourth, only stock with the status available is counted, so near-expiry batches are not included in the calculation, even though expiry is the largest contributor to the value of pharmaceutical inventory waste [1] and the problem most frequently reported by pharmacists in a study at a health institute in India [2]. Fifth, the calculation counts stock on hand but not orders already placed. Sixth, the window length, the factor of two, and the status thresholds are heuristics that were neither calibrated nor tested for sensitivity, and the recommendations were not evaluated against subsequent sales or stock levels. Seventh, the study covers only one pharmacy and about ten months of data.

Future Research

Future research should proceed in four directions. The first is outcome evaluation: recording daily stock levels so that recommendations can be replayed against staff decisions and subsequent sales, then comparing forecast error, stockout days, and expired stock with and without the module, ideally in a prospective pilot. The second is calibration: setting the window, the buffer factor, and the status thresholds per supplier or per medicine group from lead times and review periods, with a sensitivity analysis that also tests whether the 60-day trigger can be aligned with the urgency thresholds, for example by linking both to supplier lead time. The third is the forecasting method: once more than a year of sales is available, seasonal methods can be tested, and for low and intermittent demand Croston-type methods [21], [22]selected through demand categorization [23] can be compared with the simple moving average. The fourth is user and organizational impact: measuring the working time and entry errors of the form against manual copying, building on the earlier usability evaluation [10], and replicating the study in more than one pharmacy. Handling of packaging units in the recommendation, near-expiry batches, returns, and stock on order should be added along the way.

6. CONCLUSION

This study produced a medicine ordering module that connects moving average forecasting to the procurement form in a web-based pharmacy information system. The calculations of risk status and recommended quantity were consistent with an independent implementation of the same algorithm on the pharmacy's operational data, which confirms the implementation but not the operational validity of the recommendation policy, and the integration workflow removes the need to copy recommended quantities manually. The risk status and the 60-day purchase trigger are deliberately separate, and 78 of the 101 recommended medicines had the status SAFE. The history analysis shows that most historical order lines were preceded by sales, while large packaging units that require conversion are fairly dominant, which supports the design of the total-PCS field. Future research should test the recommendations against actual demand and

stock availability, calibrate the buffer and thresholds to supplier lead time, handle intermittent demand and seasonality, and measure the effect on staff working time in more than one pharmacy.

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