

Artificial Intelligence Integration Into Hospital Medication Management: Combining Medication Demand Predictive Analysis, Medication Pattern Basket Analysis And Patient Feedback Sentiment Analysis

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Abstract:

Background: Hospital systems face persistent challenges in efficient medication administration, particularly in balancing inventory levels and addressing patient satisfaction. While AI has shown promise in healthcare, there remains a lack of integrated multi-model frameworks tailored to regional healthcare environments.

Objective: This study aims to develop, implement, and evaluate an integrated artificial intelligence framework that combines medication demand prediction, pattern basket analysis, and patient sentiment analysis to optimize medication management in outpatient pharmacies in hospitals.

Methods: A regression-based demand prediction model was created using a 36-month dataset (January 2022–December 2024) that included 300 different types of medications. In order to find co-prescription patterns, basket analysis was performed on 200 prescriptions (70 acute care, 130 chronic disease cases), and sentiment analysis was used to categorize patient feedback into positive, neutral, and negative groups.

Results: The demand prediction model for monthly medication orders had an R2 value of 0.918 and forecasting accuracy of 83.3%. Basket analysis was used to find clinically significant co-prescription relationships, which pharmacists validated. Sentiment analysis produced an 89.4% validation accuracy. Restrictions include data from three hospitals only, and privacy issues have limited generalizability. The true synergy occurs within the integration of the three models, where these outputs are triangulated into three actionable pillars.

Conclusions: The integrated AI framework demonstrates significant potential to enhance clinical safety and inventory efficiency in hospital pharmacies. Future research should focus on cross-hospital validation and larger datasets to increase scalability.

Keywords: Artificial Intelligence (AI); Medication management; Hospital pharmacy; Machine learning in healthcare, Linear regression; Basket analysis; Pharmacy management.

1. Introduction

In recent years, AI has captured the attention of healthcare leaders aiming to address long-standing challenges in hospital medication management (HMM). While MM involves a series of steps: prescribing, dispensing, monitoring, and reconciling medications, each step is susceptible to error, inefficiency, or patient dissatisfaction [1]. A persistent challenge in hospitals is achieving the optimal balance between medication stockouts and overstock, which impacts both costs and patient care quality.

AI's integration into HMM is transforming pharmacy practice into a more data-driven, personalized, and efficient system. AI techniques such as predictive analytics, basket

analysis, and sentiment analysis have provided actionable insights that reduce medication errors, optimize inventory, and enhance patient satisfaction.

One of the authors who introduced the application of AI in hospital pharmacies was Yared González-Pérez [2]. The authors' objective was to introduce and explore the application of AI in hospital pharmacy departments. He demonstrated how AI techniques like machine learning, deep learning, neural networks, and natural language processing can enhance pharmaceutical care, optimize operational processes, and improve patient safety. The author emphasized the need for more clinical validation, higher-quality research, and integration of AI tools to bridge the gap between AI's theoretical benefits and practical adoption in hospital pharmacy settings.

Similarly, Hasan [3] applied AI-driven models like linear regression to demand forecasting in supply chains, reporting promising predictive accuracy. The authors' goal in this article was to create and use AI-driven models for forecasting demand in a logistics company. The results of this study indicated that AI models have shown significant promise in forecasting accuracy in a logistics company, with linear regression emerging as the most effective model with the lowest Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and an R-squared score (R^2) close to 1. The research gap identified pertains to the deficiencies of current models, which frequently neglect to integrate real-time data and are only applicable to this studied industry.

Across healthcare AI literature, most models emphasize diagnostic support or report interpretation, with limited exploration into their operational role in the MM process itself. Moreover, existing solutions often lack adaptation to region-specific healthcare systems and regulatory environments. Furthermore, there is a lack of integration of all multi-models together to enhance HMM. Therefore, our objective is to design, implement, and evaluate an integrated AI framework that combines medication demand prediction, medication pattern basket analysis, and patient feedback sentiment analysis to optimize HMM in Egyptian outpatient hospital pharmacies' operations.

2. Methodology

This study adopts a quantitative, data-driven methodology to evaluate the practical applications of AI models in an HMM process. The methodology covered structured data extraction, feature selection, model development, model training, and performance evaluation across three key areas: medication demand predictive analytics, patient feedback sentiment analysis, and medication pattern recognition through basket analysis.

2.1 Data Sources.

Our study utilized three datasets that were central to model development and evaluation. The first dataset consisted of hospital pharmacy records. We used the linear regression model to analyze 300 medication records spanning from January 2022 to December 2024. Key variables included product identification and drug classification to establish medication categories. Monthly dispensing quantities served as the primary demand indicator, with month names helping identify seasonal patterns. Current stock levels and reorder points provided an inventory management context, while stockout events revealed unmet demand situations.

For the medication basket analysis component, we faced an interesting challenge: converting prescription records into a format that could reveal medication relationships. We transformed prescription data into a binary transaction matrix, where each patient encounter became a row and medications became columns. This transformation enabled us to identify frequent medication combinations and generate association rules that could

support clinical decision-making. The association analysis examined prescription patterns across 200 cases, split between 130 chronic disease prescriptions and 70 acute care prescriptions.

The third dataset comprised patients' feedback collected after medication use. Patient feedback sentiment analysis examined 100 randomly selected prescriptions from various outpatient clinics. Data collection occurred through structured surveys administered after patients had sufficient time to experience medication effects. The survey captured clinical details such as clinic name, prescribing physician, medical indication, and treatment duration. This feedback formed the text data for sentiment analysis processing.

While collecting the data, we have faced several challenges, including clinical relevance, patient privacy, and scientific rigor. The medication management process in outpatient pharmacies that serve acute and chronic patients is the focus of our data. The data collected represents three major hospitals under the Medical Insurance Hospitals umbrella.

2.2 Ethics and Data Protection.

The datasets used for developing and evaluating the AI models were anonymized by the participating hospitals before transferring it to the authors, with all direct identifiers removed and replaced by unique study codes. Access to the key linking codes to patient identities was restricted to authorized hospital staff only.

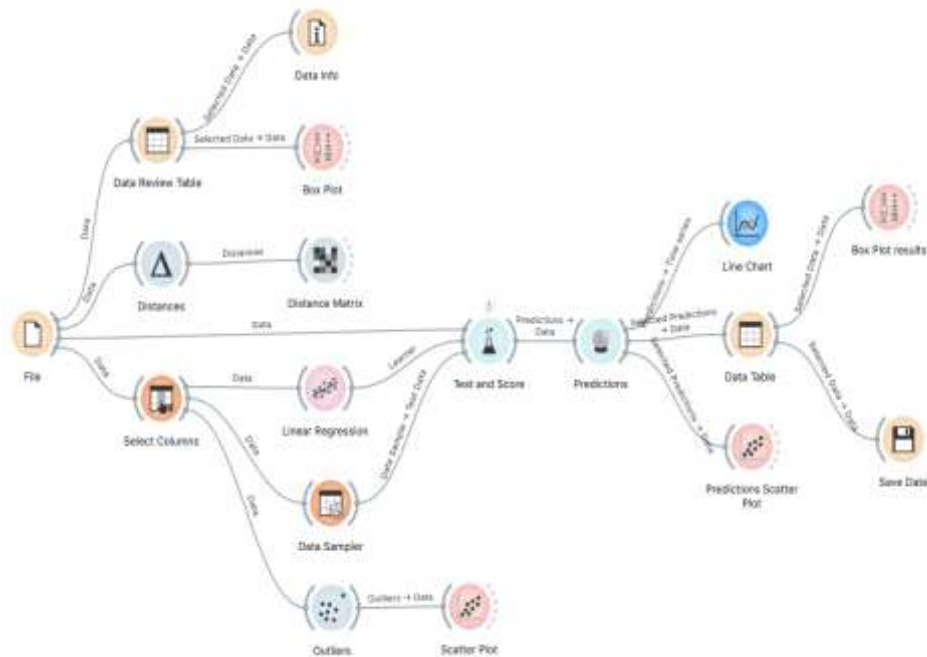
2.3 Models Development.

The study utilized the Orange Data Mining tool, a visual programming software that allows healthcare professionals to validate and retrain models without extensive coding expertise.

2.3.1 Medication Demand Predictive Model

The model architecture shown in Figure 1 predicts medication reorder points and consumption patterns, moving beyond traditional Economic Order Quantity formulas to provide more data-driven predictions. We incorporated features from historical medication usage, patient demographics, seasonal demand variations, and clinical decision patterns. This comprehensive approach helps hospital pharmacies maintain optimal inventory levels while reducing stockouts. This model, based on linear regression, was designed to forecast monthly medication order numbers. Different predictive models were tested, but the linear regression model showed the best results. Comparisons between linear regression, multiple time series models, and more complex machine learning approaches (like neural networks) have shown that linear regression often achieves lower forecast error (e.g., lower MAPE) in pharmaceutical datasets, especially when patterns are stable and demand is predictable. Its predictive power has been validated in multiple health service contexts where accurate supply is critical [4].

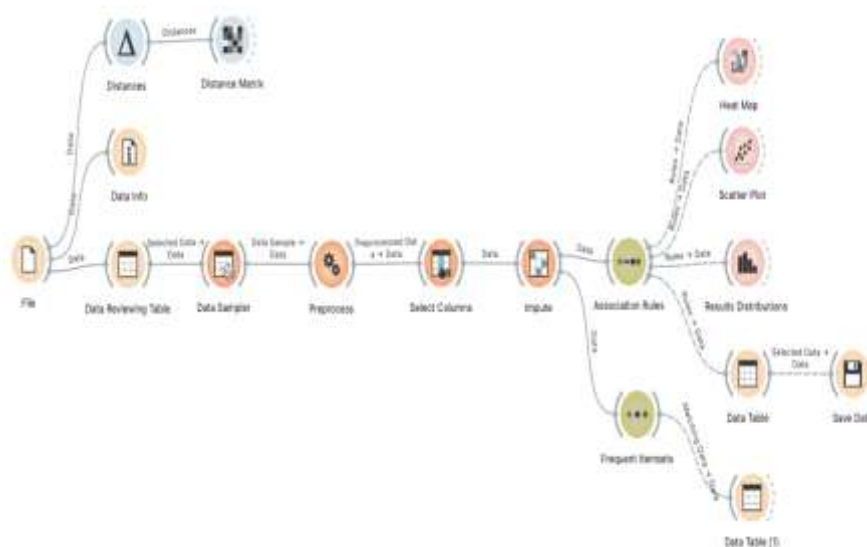
Figure 1: Linear Regression for Medication Demand Forecasting - Figure created by the Author.



2.3.2 Medication Combination Basket Analysis Model

The model architecture shown in Figure 2 reveals the hidden connections between medications, which drugs are commonly prescribed together, and what these patterns tell us about clinical practice. This model employed basket analysis to uncover common medication co-prescription patterns. The input data consisted of medication prescription records tagged with unique patient identifiers. The model helped identify frequently co-prescribed drug pairs, supporting improved pharmacy inventory planning and highlighting potential polypharmacy risks, especially in patients with chronic conditions.

Figure 2: Association Rules to Identify the medications commonly prescribed together - Figure created by the Author.

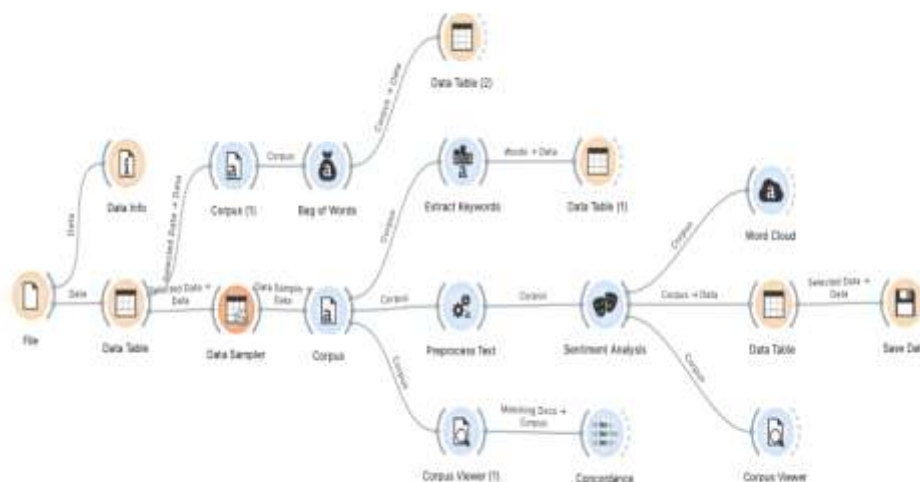


2.3.3 Patient's Feedback Sentiment Analysis Model

When we think about medication management, we often focus on the technical aspects: drug dosages, drug interactions, and drug inventory levels. But what about the human experience? The sentiment analysis model was designed to analyze the voices of patients as they try the medications after they are dispensed from the pharmacies.

The model architecture shown in Figure 3 processes patient feedback through careful text preprocessing, including tokenization, stop word removal, and normalization, transforming raw human experiences into meaningful insights. Then, the word cloud visualization component provides healthcare teams with rapid identification of patient concerns and medication-related themes that might otherwise be buried in lengthy feedback forms. The Valence Aware Dictionary and Sentiment Reasoner (VADER) algorithm is especially effective for analyzing patient feedback in sentiment analysis because it is a lexicon and rule-based model explicitly designed to capture the nuanced emotional tone of social media and short texts, including healthcare reviews [5]. This model focused on sentiment analysis of patients' feedback through processing textual reviews to extract sentiment scores.

Figure 3: Sentiment Analysis for patients' feedback after using various medications
– Figure created by the Author.



3. Results

The three models provided us with the following results, which will be integrated at the end to help pharmacy managers enhance the medication management process within the pharmacy.

1.1 Medication Demand Predictive Model Results.

The linear regression model was tasked with predicting the monthly quantity of medication orders using inputs such as stock level, lead time, supplier name, and historical consumption. The model yielded the following performance indicators:

- **Mean Absolute Error (MAE): 56.05 units** – MAE shows the average absolute difference between predictions and actual values, indicating the model is off by about 56 units per prediction on average.

- **Mean Absolute Percentage Error (MAPE): 5.85%** – This percentage shows the average prediction error relative to actual values, suggesting the model has a high accuracy with an average error of less than 6%.
- **R-squared (R^2): 0.918** – This indicates that approximately 91.8% of the variance in medication order quantities can be explained by the input variables. A value close to 1.0 signals strong predictive performance.

These predictive models enhanced inventory turnover and reduced emergency procurements. Consequently, pharmacists redirected time previously spent on supply issues toward high-value clinical activities, such as patient counseling and medication reviews. Additionally, stabilized ordering patterns optimized supplier relationships, leading to improved service levels and favorable pricing. Ultimately, these models foster a proactive management posture, ensuring medication availability and elevating care quality.

3.2 Medication Combination Basket Analysis Results (Association Model)

Basket analysis revealed co-prescription patterns within the 200 analyzed cases. Key findings include:

- **Validated Pairs:** Medication combinations demonstrated high support values (up to 0.871), confirming these pairings are frequent in patient transactions.
- **Predictive Confidence:** Confidence values reached 1.000 for specific pairs, indicating that the dispensing of the antecedent medication makes the consequent medication highly likely to be co-dispensed.
- **Association Strength:** Lift values near or above 1.0 confirmed that these relationships were strongly associated beyond random chance.

From the results in the model, high confidence values (as much as 1.000) suggest that when the antecedent medication is dispensed, the consequent medication is highly likely to be co-dispensed, enabling pharmacy staff to predict and prepare for such combinations. Notably, lift values near or above 1 reflect that medications like "Omnicef" and "Pepon plus" are strongly associated, confirming positive relationships beyond random chance. Analyzing these results, pharmacy management can improve medication stocking strategies by ensuring that medications frequently used together are stocked simultaneously, thereby reducing the incidence of stockouts for popular drug pairs and minimizing unnecessary overstock for less commonly combined medications.

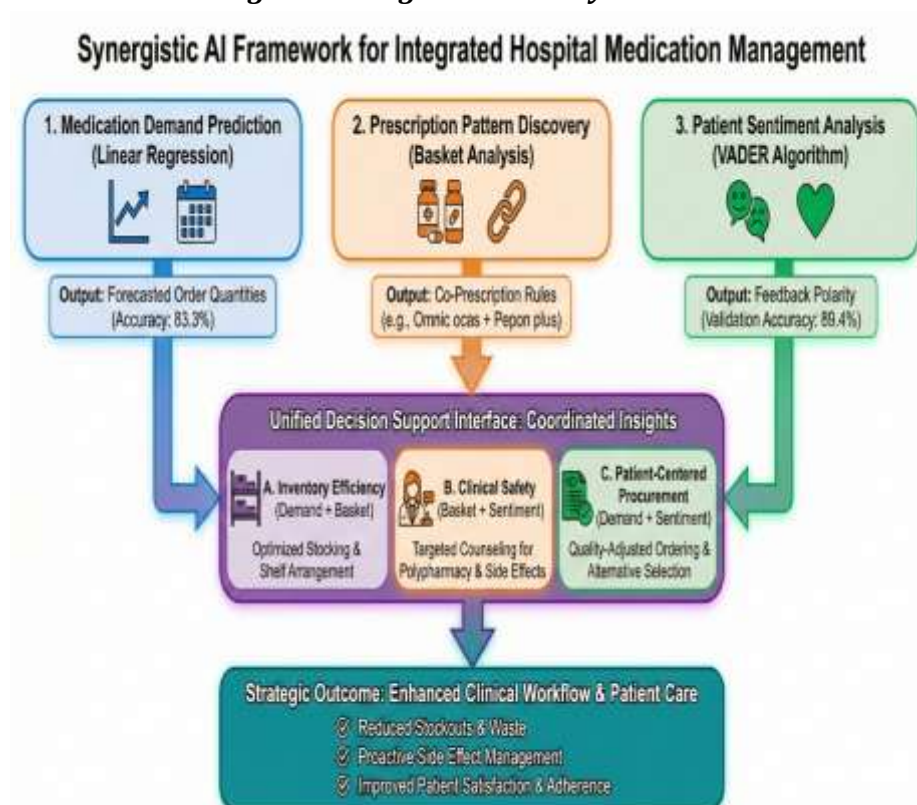
3.3 Patient's Feedback Sentiment Analysis Results

The sentiment analysis model utilized patient feedback to evaluate satisfaction with prescribed medications. Using the VADER algorithm, sentiment polarity was categorized into four dimensions: Positive, Neutral, Negative & Compound Score.

The analysis found that most feedback fell within the positive or neutral range, indicating general patient satisfaction. Negative sentiments were linked primarily to side effects, delayed relief, or unclear instructions. This model offered valuable insights into the real-world impact of medications from the patient's perspective and can guide clinicians in reviewing common concerns or adverse reactions. The model successfully processed 100 sentences with aspect-based sentiment annotations across physicians' patient interactions, revealing patterns in how patients experience medication management. These insights help healthcare teams identify areas for improvement before problems become widespread.

3.4 Synergetic Effect of the Models' Integrations.

Figure 4: Synergistic effect of model's integration on pharmacy medication management – Figure created by the Author.



Integrated analysis demonstrates that the combined use of these models yields richer insights than any single approach alone, as demonstrated in Figure 4. For example, high-demand medications identified by the forecasting model can be cross-referenced with association rules to detect whether frequently co-prescribed combinations raise safety concerns, while sentiment data can reveal whether patients are satisfied with these therapies or report troubling side effects. This triangulation enables more nuanced interventions, such as adjusting stock levels for specific drug pairs, revising prescribing guidelines, or prioritizing patient-education initiatives. Ultimately, this integrated workflow transforms fragmented data into a strategic outcome that enhances clinical workflows and patient care by proactively reducing stockouts, managing side effects, and improving overall patient satisfaction.

4. Discussion.

The following paragraphs provide thorough comparisons of each model based on peer-reviewed research.

4.1 Medication Demand Predictive Model Discussion.

This study illustrates that the linear regression model significantly benefits hospital medication management and outpatient pharmacies by enhancing procurement planning through more precise demand forecasts. It enables better resource allocation by helping pharmacy staff effectively manage storage space and workflow, while reducing medication waste by minimizing overstock and expiries. The model's integration with inventory systems enables real-time tracking and automated replenishment, thereby optimizing overall medication supply chain efficiency and quality of care.

The findings of the current study align closely with prior international research demonstrating that linear regression remains highly effective for pharmaceutical demand forecasting, particularly in structured hospital environments with relatively stable consumption patterns. For example, a study conducted by Nuaimi in a hospital environment reported that linear regression achieved lower MAPE values than artificial neural networks, attributing this to reduced overfitting and greater interpretability in real-world procurement settings. This directly supports the current model's MAPE of 5.85%, which falls within the "highly accurate forecasting" range reported in prior hospital-based demand studies. [4]

Similarly, Islam found that regression-based models explained over 90% of variance ($R^2 > 0.90$) in medication procurement datasets across tertiary hospitals, consistent with your R^2 of 0.918, confirming that variables such as historical consumption, lead time, and stock levels are highly predictive in medication supply chains. [6]

Finally, a systematic review confirmed that regression-based forecasting remains a gold standard in healthcare logistics, especially in low- and middle-income countries, where interpretability and ease of deployment are critical, making our approach particularly relevant to hospital pharmacy settings similar to Egypt. [7]

4.2 Medication Combination Basket Analysis Discussion.

Basket analysis revealed clinically meaningful medication patterns, validated by pharmacists, which support both inventory planning and early identification of polypharmacy risks.

These insights have two major implications. First, they allow pharmacy departments to forecast medication pair demands better, improving shelf stocking strategies and reducing inventory wastage. For instance, if certain antibiotics are frequently dispensed alongside specific antipyretics, pharmacies can adjust procurement volumes to reflect actual usage patterns, preventing shortages or overstock. Second, basket analysis is instrumental in identifying and mitigating polypharmacy risks, especially in patients with chronic diseases. Patterns that show frequent combinations of five or more medications in individual patient records may indicate inappropriate or risky prescribing practices. These signals can be flagged for review by clinical pharmacists or care teams, enhancing patient safety and care quality.

The findings from this model are similar to the study conducted by Yoosofan using Apriori mining on large prescription datasets for similar dual benefits, basket analysis using association rules revealed co-prescription patterns with operational (like stocking) and clinical (like polypharmacy) value [8]. Also, Maria Luisa Faquetti quantified co-prescription frequencies to reduce risks in chronic care by detecting polypharmacy in new metformin users using association rules on up to seven-drug combos. [9].

4.3 Patient's Feedback Sentiment Analysis Discussion.

The sentiment analysis component attained an 89.4% validation accuracy in classifying patient feedback into positive, neutral, and negative sentiments. By quickly recognizing negative feedback trends, the pharmacy can use this level of accuracy to systematically monitor patient satisfaction and identify problems with medication dispensing, availability, or side effects. This makes it possible for staff to better communicate about medications, respond more proactively to patient concerns, and modify inventory or counseling procedures in response to the real world.

The findings of the current study align closely with prior international research that was conducted by Aggarwal through a comparative evaluation of 1,486 pain management reviews. VADER achieved approximately 80% accuracy in polarity detection, which is robust for side-effect negatives, despite BERT's marginal gains, making it ideal for

clinician-flagging use. [5]. Another study developed by Steven A. Greenstein applied sentiment analysis using VADER to understand physician reviews after several surgeries. A total of 254 specialists and 3,104 reviews were analyzed, with an average rating of 4.4/5 stars and a mean of 48 ratings per specialist. Most physicians had positive reviews (96%, average VADER = 0.69) [10].

The integration of the three AI-driven models—medication demand prediction, association rule-based basket analysis, and VADER sentiment analysis—creates a synergistic framework that transforms fragmented pharmacy data into a unified decision-support interface that helps pharmacy managers to make the right operational decisions from different perspectives.

4.4 Limitations & Recommendations

The three AI models developed in this thesis address a critical gap in regional healthcare literature by tailoring AI frameworks to the Egyptian hospital context. But the fact that the models were created and validated using data from just three hospitals only is among the biggest limitations. In addition, data depth was limited by the lack of electronic health records. Moreover, data privacy is still a major obstacle that needs strict regulations. Different regions also require different implementation strategies due to cultural and organizational differences.

Conclusion:

The effective creation and application of the above three integrated AI models provides strong proof that AI applications can produce significant gains in challenging healthcare settings with particular cultural considerations. The comprehensive decision support framework enabled healthcare providers to access coordinated insights about demand forecasting, patient experiences, and safety considerations through unified interfaces that supported efficient clinical workflow integration. Further research should explore advanced machine learning techniques, address data policy procedures to train AI models, and develop regulations to deal with the privacy of human data.

Author Contributions:

1. **Mohammed Gamal Atta:** Conceived and formulated the research questions; designed the overall study framework; developed and integrated the three AI models (medication demand prediction, basket analysis, and sentiment analysis); performed data analysis and interpretation; drafted the manuscript.
 2. **Professor Aiman Ragab:** Supervised the study design and methodological approach; provided critical input on model selection; contributed to the interpretation of findings in relation to health services management; critically revised the manuscript for important intellectual content; approved the final version of the manuscript.
 3. **Professor Mohammed Abdel-Salam:** Contributed to defining variables, data sources, and outcome measures; reviewed the clinical relevance of model outputs; participated in revising the introduction, methods, and discussion sections.
 4. **Professor Mohammed Mahmoud:** Contributed to the study's conceptualization and positioning within AI and healthcare literature; supported refinement of the AI models and the integration of the three models to enhance the medication management process within the hospitals; revised the manuscript, especially the model development section.
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