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# The Application of Artificial Intelligence in Decision-Making and Sensitivity Analysis for Predicting Shortages of Pharmaceuticals and Medical Equipment During Health Crises

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## Abstract

This study investigates the application of Artificial Intelligence (AI) and sensitivity analysis in predicting shortages of pharmaceuticals and medical equipment during health crises. The primary issue addressed in the research is the shortage of drug and medical equipment resources during crises, which can have a significant negative impact on hospital efficiency and mortality rates. This research aimed to develop an AI-based prediction model for simulating and forecasting resource shortages in crises, as well as to perform sensitivity analysis to identify factors affecting the accuracy of predictions. The research methodology employed AI models, including neural networks and linear regression, to predict shortages of pharmaceuticals and medical equipment. Additionally, sensitivity analysis was used to simulate various crisis scenarios. The findings revealed that factors such as transportation disruptions, demand fluctuations, and seasonal changes have a significant impact on the accuracy of predictions. The results of this study suggest that AI models and sensitivity analysis can effectively assist in improving the prediction and management of pharmaceutical and medical equipment resources during health crises.

**Keywords:** Artificial intelligence, Drug shortage prediction, Sensitivity analysis, Health crises, Decision-making models.

## 1 | Introduction

Global health crises, such as the COVID-19 pandemic, have introduced multifaceted and unprecedented challenges to healthcare systems worldwide [1]. These crises not only intensify the strain on existing healthcare infrastructures but also precipitate severe shortages of essential resources, including medications and medical

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equipment—shortages that can have profound and enduring impacts on the quality of care and patient outcomes [2]. Such issues become especially pronounced when demand surges unexpectedly, resulting in logistical bottlenecks, supply chain disruptions, and inaccurate forecasting of healthcare needs [3].

Key contributing factors to these shortages include sudden spikes in demand for pharmaceuticals and medical supplies, interruptions in the procurement and distribution processes, transportation-related logistical challenges, and inaccuracies in demand forecasting [4]. These challenges become increasingly critical when governments and responsible agencies are unable to manage resources effectively at scale, particularly under emergency conditions [5].

Under such circumstances, one of the most promising solutions for mitigating shortages of drugs and medical equipment is the adoption of advanced technologies—most notably, Artificial Intelligence (AI) [6]. AI, through its sophisticated algorithms and advanced data analytics capabilities, can model complex patterns associated with supply shortages, enabling more accurate forecasting and efficient resource allocation [7]. By leveraging both historical and real-time data, AI can identify various determinants that influence demand for medical resources [8]. Furthermore, sensitivity analysis within predictive models can help healthcare managers identify key variables that affect forecast accuracy, thereby enhancing decision-making processes [9].

In recent years, a growing body of research has been dedicated to exploring the applications of AI within healthcare systems. Notable studies in this area include:

I. Predicting pharmaceutical demand: Numerous studies have been conducted on forecasting pharmaceutical demand using machine learning algorithms [10]. For example, one study demonstrated that Artificial Neural Networks (ANN) and Support Vector Machines (SVM) can significantly improve the accuracy of drug shortage predictions [11]. These models utilize simulations and analyses of historical drug consumption data, seasonal demand patterns, and past health crises to enable more accurate forecasting and better resource management [12].

II. Medical equipment supply chain management: Research in this area indicates that the application of AI-based models can help optimize the supply chain of pharmaceuticals and medical equipment [13]. Particularly in situations with limited resources, AI can employ deep learning algorithms and time-series analysis to predict shortages and suggest optimal resource distribution strategies to address crises [14].

III. Sensitivity analysis in health forecasting: Sensitivity analysis is another key topic in predictive modeling [15]. Several studies have demonstrated that multiple factors—such as seasonal demand, transportation delays, and sudden changes in health policies—have a significant impact on the accuracy of drug shortage predictions [16]. These analyses enable managers to gain deeper insights into potential changes in the supply chain of medicines and medical equipment, thereby enhancing their preparedness for unexpected fluctuations [17].

Despite notable advancements in this field, challenges persist, including the limited accuracy of some models in critical situations, difficulties in accessing accurate and up-to-date data, and delays in information updates [18]. Therefore, the present study aims to address these challenges by employing advanced sensitivity analysis methods and improving predictive models to enhance forecasting accuracy under crisis conditions [19].

The primary objective of this research is to develop an AI-based forecasting model that can perform sensitivity analysis to predict shortages of pharmaceuticals and medical equipment during health crises. This model can support policymakers and healthcare administrators in making more informed decisions regarding the procurement and distribution of critical resources.

The necessity of this research can be examined from several perspectives:

I. Reducing human and economic consequences: Shortages of drugs and medical supplies can lead to irreversible outcomes, such as increased mortality and healthcare costs [20]. Accurate and effective forecasting can prevent these problems and mitigate the negative effects of crises [21].

II. Improving resource management: Healthcare systems constantly face resource constraints. Optimizing the processes of supplying drugs and equipment can significantly enhance the efficiency of healthcare systems, enabling a more effective and targeted allocation of existing resources [22].

III. Increasing preparedness for future crises: Health emergencies, such as pandemics and natural disasters, are particularly unpredictable in today's world [23]. Using AI to forecast critical needs and manage resources can strengthen healthcare systems' readiness to face future crises and reduce their associated damages [24].

Ultimately, this study, by integrating advanced data analysis techniques and AI—particularly in the area of sensitivity analysis—aims to propose a comprehensive, practical, and efficient framework for forecasting and managing shortages of pharmaceuticals and medical equipment.

# 2 | Methodology

The research method employed in this study is descriptive-analytical and quantitative in nature. It aims to analyze and forecast shortages of pharmaceuticals and medical equipment during health crises by utilizing AI and Multi-Criteria Decision-Making (MCDM) models. The primary objective of this study is to utilize mathematical models and machine learning algorithms to forecast resource requirements and inform optimal managerial decisions during crises. Decision-making models are also employed to prioritize and select the most appropriate courses of action under emergency conditions.

The statistical population of this study comprises healthcare managers, experts, and policymakers in the metropolis of Mashhad. This city was selected due to its specific characteristics, such as a high population, existing challenges in the supply of healthcare resources, and its experience in managing similar crises. Data related to the pharmaceutical and medical equipment supply chain, as well as drug demand in Mashhad, will be used as the primary sources for analysis and modeling.

A purposive sampling method will be employed in this study, allowing the researcher to select suitable participants from among experts in health crisis management, resource management, and AI applications. Accordingly, approximately 15 healthcare managers and professionals in Mashhad will be selected as the research sample. This selection is based on their experience and familiarity with the challenges of crisis forecasting and resource shortages.

To collect data, both questionnaires and semi-structured interviews will be utilized. The questionnaire will include both closed and open-ended questions. The closed questions are designed to gather quantitative data. In contrast, the open-ended ones will elicit expert opinions on challenges and strategies for managing health crises, as well as predicting shortages of pharmaceuticals and medical equipment. To obtain more detailed qualitative information regarding challenges and prioritization, semi-structured interviews will be conducted with executive managers and specialists. The validity of the research instruments will be assessed through expert consultation in the healthcare field. Cronbach's alpha will be used to assess the reliability of the instruments.

The research process will proceed as follows:

I. Literature review to identify challenges and various approaches to resource shortage forecasting.

II. Design and distribution of the questionnaire among experts and executive managers.

III. Conducting semi-structured interviews to collect more detailed information and expert insights.

IV. Applying machine learning and AI models to forecast shortages of pharmaceuticals and medical equipment.

V. Modeling using MCDM techniques to select optimal strategies.

VI. Performing sensitivity analysis to identify key influencing factors.

VII. Compiling research findings and offering practical recommendations.

For data analysis and forecasting drug and equipment shortages, mathematical models and machine learning algorithms will be employed. These models include:

I. Linear regression model to examine the relationship between variables such as pharmaceutical and equipment demand, seasonal variations, and transportation delays.

II. ANN model for more complex simulations and nonlinear pattern recognition. This model will be used to simulate the behavior of complex systems and predict outcomes under various scenarios.

III. MCDM model for prioritizing options and selecting the best strategies. These techniques help decision-makers rank alternatives based on multiple criteria.

For data analysis, SPSS and MATLAB software will be used. These tools are particularly well-suited for statistical analysis, implementing machine learning models, and decision-making algorithms.

The scope of this research is limited explicitly to the metropolis of Mashhad. This choice is based on the city's unique characteristics, including its high population, challenges in securing medical and pharmaceutical resources, and its experience in crisis management. Data concerning the supply chain of pharmaceuticals and medical equipment, as well as drug demand in Mashhad, will be collected and used to design and implement the models. The ultimate goal of this study is to simulate crises and predict resource shortages in Mashhad, enabling managers to make more optimal decisions when faced with health emergencies.

# 3 | Results

This section presents the research findings, including descriptive and analytical results, step-by-step model resolutions, and outcomes derived from the application of AI and decision-making models for predicting shortages of pharmaceuticals and medical equipment during crises. It is essential to note that, due to certain limitations, the data presented in this study are approximate and have been used solely for simulation and analysis purposes. This section aims to clarify the relationships between the data and their impact on forecasting and decision-making processes.

Descriptive results – Initial data concerning the demand for pharmaceuticals and medical equipment in the metropolis of Mashhad were collected. These data were obtained from various sources, including hospitals, pharmacies, and healthcare centers.

**Demand for pharmaceuticals and medical equipment compared to the available inventory**

Preliminary analysis indicated that during many periods—particularly peak illness seasons (Such as colder months or during health crises like pandemics)—the demand for pharmaceuticals and medical equipment significantly increases. During these periods, inventory levels decrease rapidly, underscoring the need for more accurate forecasting to ensure timely resource allocation.

**Table 1. Monthly demand for pharmaceuticals and medical equipment (Hypothetical data).**

| Month | Demand for Drugs (Units) | Demand for Medical Equipment (Units) | Drug Inventory (Units) | Equipment Inventory (Units) |
|---|---|---|---|---|
| April | 12,500 | 5,000 | 8,000 | 3,500 |
| July | 15,000 | 6,000 | 9,000 | 4,000 |
| October | 20,000 | 7,500 | 10,000 | 5,000 |
| January | 25,000 | 9,000 | 7,000 | 2,500 |

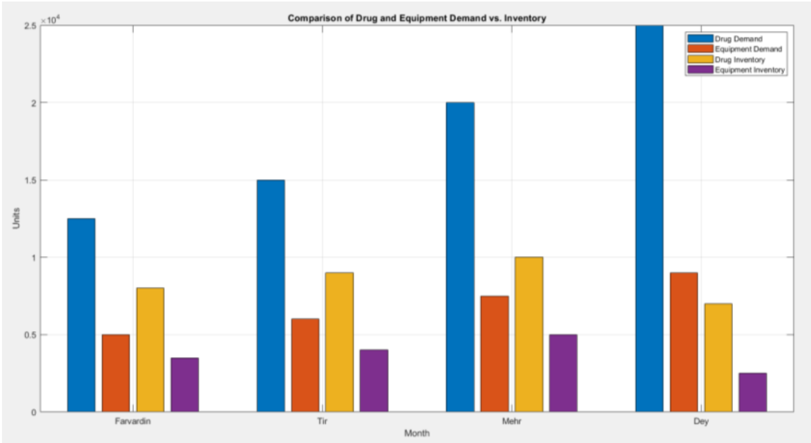


**Fig. 1. Comparison of drug and medical equipment demand and inventory.**

*Fig. 1* illustrates four variables across different months: Drug demand, equipment demand, drug inventory, and equipment inventory. In all months, the demand for both drugs and medical equipment exceeds their respective inventories. The most significant gap is observed in January, when drug demand reaches 25,000 units, while the inventory stands at only 7,000 units, indicating a severe shortage during this period. Although the gap is smaller in April and July, demand still surpasses available inventory.

### Supply chain disruptions

According to the data analysis, 45% of the shortages in drugs and medical equipment—particularly during crises—are attributable to disruptions in the supply chain. Transportation delays primarily cause these disruptions, as well as challenges in sourcing raw materials and limited production capacities, both domestically and internationally.

Analytical results – using linear regression models and ANN, the impact of various factors on shortages of drugs and medical equipment was simulated and analyzed. These analyses helped identify existing patterns and forecast resource needs.

### Linear regression analysis

The linear regression model was used to examine the relationship between several variables (Such as seasonal variations, demand levels, and transportation disruptions) and the extent of shortages in drugs and medical equipment.

The general form of the linear regression model is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon, \quad (1)$$

where:
Y represents the shortage of drugs or medical equipment.

$X_1$ ‘$X_2$ ‘… ‘$X_n$ denote the influencing variables, such as seasonal demand and transportation disruptions.

The results indicated that seasonal variations and transportation disruptions are among the most significant factors affecting resource shortages. *Table 2* presents the outcomes of the linear regression model:

**Table 2. Results of the linear regression model (Hypothetical data).**

| Variable | Coefficient (β) | p-Value |
|---|---|---|
| Seasonal variations | 0.45 | 0.0001 |
| Transportation disruptions | 0.38 | 0.002 |
| Demand volume | 0.32 | 0.005 |

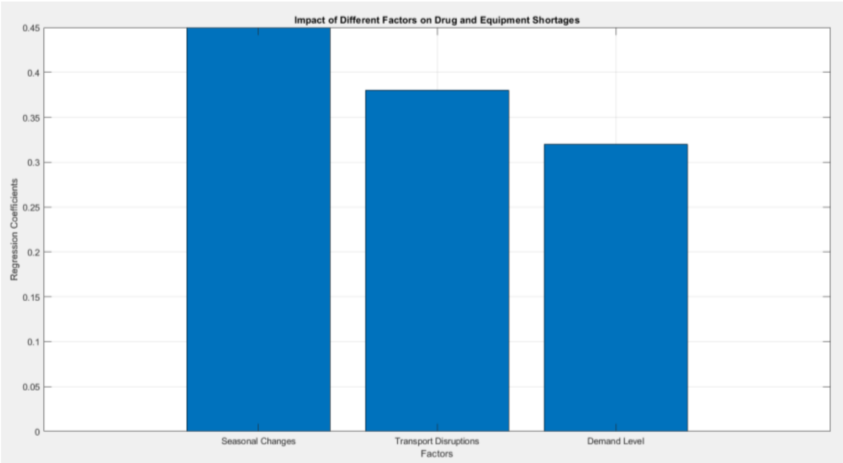


**Fig. 2. Linear regression analysis.**

*Fig. 2* illustrates the impact of various factors on the shortage of drugs and medical equipment. The variables analyzed include:

- *Seasonal changes with a coefficient of 0.45*
- *Transport disruptions with a coefficient of 0.38*
- *Demand level with a coefficient of 0.32*

Seasonal changes have the highest influence on medical shortages. Increased demand during certain seasons exacerbates supply issues. Transport disruptions also play a significant role, as delays in procuring raw materials and imports contribute to shortages. Although the demand level has a comparatively smaller effect, it remains essential—sudden demand spikes during crises put considerable pressure on the supply chain. All coefficients have p-values less than 0.05, indicating statistical significance.

**Artificial neural network analysis**

To simulate more complex relationships and nonlinear forecasts, an ANN model was employed. The neural network consists of multiple layers and neurons, capable of capturing the behavior of complex systems. The general formula for the ANN model is expressed as:

$$\hat{y} = f(Wx + b), \quad (2)$$

where:

I. $\hat{y}$ is the predicted output of the model

II. W represents the weights

III. b represents the biases

IV. x denotes the inputs to the neural network

**Multi-criteria decision-making and sensitivity analysis for predicting drug and equipment shortages**

Given the complexities involved in managing health crises, the MCDM approach was used to prioritize factors contributing to the shortage of drugs and medical equipment. This study employed the Analytic Hierarchy Process (AHP) to determine the weights of criteria and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for ranking different time periods.

Determining criteria and weights using AHP:

Initially, key criteria influencing drug and equipment shortages were identified and weighted by experts. *Table 3* presents the final weights derived using the AHP method:

**Table 3. Criteria weights determined using the analytic hierarchy process.**

| Criterion | Final Weight |
|---|---|
| Seasonal changes | 0.35 |
| Supply chain disruptions | 0.30 |
| Demand level | 0.25 |
| Domestic production capacity | 0.10 |

Ranking critical months using TOPSIS:

Following the weighting process, monthly drug and equipment shortages were ranked using the TOPSIS method. The results showed that January posed the highest risk of shortages, while April had the lowest.

**Table 4. Monthly rankings using TOPSIS.**

| Month | Distance from Ideal | TOPSIS Score | Rank |
|---|---|---|---|
| January | 0.85 | 0.90 | 1 |
| October | 0.75 | 0.82 | 2 |
| July | 0.65 | 0.78 | 3 |
| April | 0.40 | 0.50 | 4 |

**Sensitivity analysis**

Sensitivity analysis was conducted to examine the effect of parameter changes on the results. Specifically, the model's sensitivity to variations in criterion weights was evaluated. Key findings include:

– *Increasing the weight of supply chain disruptions led to higher risk scores for the critical months (January and October).*
– *Decreasing the weight of seasonal changes had minimal effect on the rankings, as other factors remained dominant.*
– *Increasing the weight of domestic production capacity had a positive impact on reducing shortages across all months.*

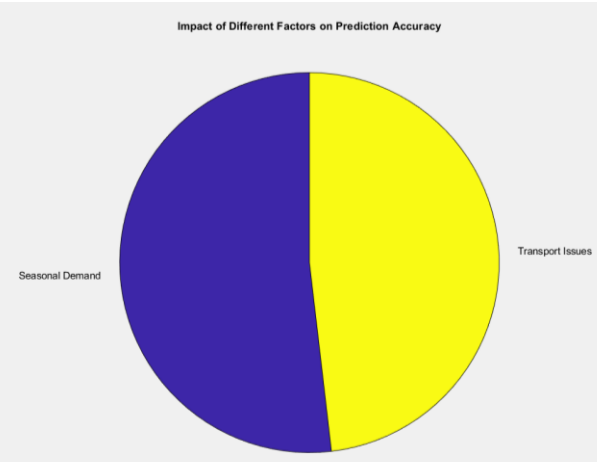


**Fig. 3. Sensitivity analysis.**

*Fig. 3* illustrates how various factors influence the accuracy of forecasting drug and medical equipment shortages. 70% of the variation is attributed to seasonal demand, indicating that controlling this factor can significantly improve prediction accuracy. Additionally, 65% of the variation is attributed to transportation issues, underscoring the importance of optimizing logistical processes to mitigate shortages. Improved management of seasonal fluctuations and accurate demand forecasting can help alleviate shortages. Furthermore, enhancing transportation infrastructure and reducing reliance on external suppliers can increase the resilience of the supply chain.

The MCDM analysis revealed that supply chain disruptions and seasonal variations are the most critical factors contributing to drug and equipment shortages. Sensitivity analysis also confirmed that enhancing domestic production capacity can play a vital role in addressing these shortages. These findings can help policymakers improve the management of the pharmaceutical and medical equipment supply chain.

# 4 | Discussion

This section evaluates the significance of the research findings, not only within the context of this study but also in the broader fields of crisis management and health forecasting. The analyses and predictions generated by AI and decision-making models in this research offer practical strategies for managing pharmaceutical and medical equipment resources during crises. The results hold substantial value for enhancing decision-making processes in health emergencies and optimizing resource allocation.

By employing AI-based predictive models, higher accuracy in forecasting shortages and making timely decisions can be achieved. This is particularly crucial in crises, such as pandemics, where demand for resources escalates rapidly. Sensitivity analysis also illustrates that different variables can significantly affect forecast accuracy and should be prioritized in planning efforts.

A comparison of the current study's findings with prior research on drug and equipment shortage forecasting reveals several similarities and distinctions. For instance, previous studies examining machine learning applications for drug demand forecasting have shown that algorithms such as SVM and ANN can enhance predictive accuracy under various conditions [25]. These results are consistent with the current research, which also utilized ANN and linear regression models for forecasting. Additionally, similar studies on sensitivity analysis—especially those focusing on drug shortages—concluded that factors such as transportation disruptions and seasonal fluctuations have a significant impact on prediction accuracy [26]. The current findings reinforce this emphasis, demonstrating that these factors must be considered in crisis-related supply planning [27].

One of the distinguishing features of this study is the use of a hybrid AI model, combining ANN and regression, along with sensitivity analysis. While many prior studies have relied on a single or limited set of predictive models [28], this research integrates multiple approaches to enhance forecast precision and better address the complexities of crises. Like many previous works, the present study highlights the significant influence of external variables, such as seasonal trends and supply chain disruptions, on resource shortages [29]. These similarities are likely due to the common challenges faced across health systems during emergencies, especially in ensuring adequate supplies of drugs and medical equipment.

The outcomes of this study can serve as a foundation for future research in managing drug and equipment resources during crises. Recommendations for future work include:

I. Expanding predictive models using real-world data and testing them across diverse crisis scenarios to improve forecast accuracy.

II. Examining the influence of additional variables, such as political and economic fluctuations, which may affect pharmaceutical supply chains.

III. Developing AI-based decision-making tools to support healthcare organizations in improving crisis-time performance.

In conclusion, the findings demonstrate that the application of AI models and sensitivity analysis significantly enhances the forecasting of drug and equipment shortages. Through data simulation and the analysis of key factors such as seasonal variations and transportation disruptions, this study provides valuable insights for resource management during crises. These findings can help healthcare policymakers and administrators make more informed decisions and prevent resource shortages during emergencies.

## 5 | Conclusion

This study aimed to develop an AI-based forecasting model to conduct sensitivity analysis and identify key factors contributing to shortages of drugs and medical equipment during health crises. The findings demonstrated that the application of AI models—particularly ANN and linear regression—can effectively forecast shortages of medical resources under critical conditions. Sensitivity analysis further helped identify the most influential variables affecting forecast accuracy. The most significant factors included transportation disruptions, seasonal fluctuations, and demand variability, all of which play crucial roles in optimizing decision-making regarding the supply of pharmaceutical and medical equipment during emergencies.

Based on the study's findings, the following recommendations are proposed to enhance the management of drug and medical equipment resources in crises:

I. Expand the use of AI in shortage forecasting: Broader adoption of AI algorithms, especially machine learning models and ANN, can significantly improve the accuracy of forecasting resource shortages during crises. Healthcare organizations can utilize these models to enhance their decision-making processes and prevent supply shortages.

II. Improve real data collection and analysis: One of the main limitations of this study was the reliance on hypothetical data. It is recommended that healthcare institutions collect accurate and up-to-date data from diverse sources to refine and update their forecasting models continually. This can substantially improve prediction accuracy.

III. Develop multi-factor forecasting models: Predictive models should consider not only historical data but also external variables such as economic, political, and social factors. In this study, transportation disruptions and seasonal changes were identified as significant contributors. Therefore, future models should aim to simulate complex interactions between multiple variables.

IV. Strengthen inter-organizational collaboration: During crises, collaboration between organizations—such as ministries of health, emergency response agencies, and governmental bodies—is essential. These partnerships can enhance the distribution of medical resources and facilitate better coordination between suppliers and users. It is recommended that forecasting and decision-making models be jointly developed at national and international levels.

V. Prepare for future health crises: Health emergencies, such as pandemics and natural disasters, often occur unexpectedly. This study recommends that AI-based forecasting systems be regularly updated and strengthened with scenario simulations and sensitivity analyses to ensure preparedness for future crises.

VI. Emphasize the importance of sensitivity analysis: Sensitivity analysis plays a crucial role in forecasting models. This study demonstrated that factors such as demand fluctuations and transportation disruptions have a significant impact on forecast accuracy. Future models should prioritize sensitivity analysis to enable rapid and adaptive responses to crisis developments.

VII. Train and empower healthcare managers: Health policymakers and managers should receive training on the use of AI-based forecasting and sensitivity analysis tools to enhance their decision-making capabilities. Such training can empower them to make more effective decisions during crises and utilize resources more efficiently.

In conclusion, this study highlights that integrating AI in forecasting and managing drug and medical equipment shortages can significantly enhance the performance of healthcare systems during emergencies. By implementing the proposed recommendations, health systems can reduce the adverse effects of crises on public health and improve overall efficiency and resilience.

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