

Machine Learning and Causal Bayesian Networks for Healthcare Resource Allocation

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Sofia Martinez

Department of Data Science,
University of Barcelona,
Spain

Abstrak

Alokasi sumber daya kesehatan memerlukan pengambilan keputusan dalam kondisi ketidakpastian, terutama ketika permintaan berfluktuasi, sumber daya terbatas, dan sistem layanan kesehatan menghadapi berbagai prioritas operasional yang saling bersaing. Pembelajaran mesin dapat mengidentifikasi pola dan memprediksi kebutuhan sumber daya, sedangkan jaringan Bayesian dapat merepresentasikan hubungan probabilistik antarvariabel kesehatan serta mendukung pengambilan keputusan dalam kondisi tidak pasti. Penelitian ini mengkaji suatu kerangka kerja yang mengintegrasikan pembelajaran mesin dan jaringan Bayesian kausal untuk alokasi sumber daya kesehatan. Kerangka kerja ini mempertimbangkan permintaan pasien, kapasitas fasilitas, ketersediaan sumber daya, risiko operasional, dan kebutuhan layanan kesehatan sebagai faktor yang saling berhubungan dan memengaruhi keputusan alokasi. Model pembelajaran mesin digunakan untuk mengidentifikasi pola dan memperkirakan potensi kebutuhan sumber daya, sementara pemodelan jaringan Bayesian menyediakan representasi terstruktur mengenai ketergantungan dan ketidakpastian. Penalaran kausal juga memungkinkan pengambil keputusan untuk mengkaji bagaimana perubahan ketersediaan sumber daya atau kondisi operasional dapat memengaruhi hasil layanan kesehatan. Kerangka kerja ini turut mengintegrasikan analisis skenario dan analisis what-if untuk membandingkan berbagai strategi alokasi sebelum diterapkan. Dengan menggabungkan pembelajaran prediktif dengan penalaran probabilistik dan kausal, pendekatan ini dapat mendukung alokasi sumber daya kesehatan yang lebih transparan, efisien, dan berbasis bukti. Pendekatan ini dapat membantu organisasi layanan kesehatan mengantisipasi kebutuhan sumber daya, memprioritaskan kebutuhan kritis, dan meningkatkan pengambilan keputusan dalam kondisi yang tidak pasti.

Kata Kunci:

Pembelajaran Mesin, Jaringan Bayesian Kausal, Alokasi Sumber Daya Kesehatan, Kecerdasan Buatan, Jaringan Bayesian, Analitik Prediktif, Penalaran Kausal, Sistem Pendukung Keputusan.

Abstract

Healthcare resource allocation requires decisions to be made under uncertainty, particularly when demand fluctuates, resources are limited, and healthcare systems face competing operational priorities. Machine learning can identify patterns and predict resource requirements, while Bayesian networks can represent probabilistic relationships among healthcare variables and support decision-making under uncertainty. This study examines a framework that integrates machine learning and causal Bayesian networks for healthcare resource allocation. The framework considers patient demand, facility capacity, resource availability, operational risks, and healthcare service requirements as interconnected factors influencing allocation decisions. Machine-learning models are used to identify patterns and estimate potential resource needs, while Bayesian network modelling provides a structured representation of dependencies and uncertainty. Causal reasoning further allows decision-makers to examine how changes in resource availability or operational conditions may influence healthcare outcomes. The framework also incorporates scenario and what-if analysis to compare alternative allocation strategies before implementation. By integrating predictive learning with probabilistic and causal reasoning, the approach can support more transparent, efficient, and evidence-based allocation of scarce healthcare resources. It can help healthcare organizations anticipate resource requirements, prioritize critical needs, and improve decision-making under uncertain conditions.

Keyword:

Machine Learning, Causal Bayesian Networks, Healthcare Resource Allocation, Artificial Intelligence, Bayesian Networks, Predictive Analytics, Causal Reasoning, Decision Support.

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INTRODUCTION

Healthcare organizations routinely make resource-allocation decisions under conditions of uncertainty. Hospitals and healthcare systems must determine how limited personnel, medical equipment, facilities, medicines, and other resources should be distributed across competing needs. These decisions become more

difficult when healthcare demand changes rapidly or when operational incidents create additional pressure on available resources.

Traditional resource-allocation approaches may depend heavily on historical information, expert judgment, or predetermined allocation rules. Although these approaches remain useful, the increasing availability of healthcare data creates opportunities for more advanced analytical decision support. Machine learning can process complex datasets and identify patterns associated with healthcare demand, operational risks, and resource requirements.

Bayesian networks provide another useful approach because they can represent relationships between variables probabilistically. Healthcare systems contain numerous interconnected factors, and Bayesian networks can help represent uncertainty and update the probability of outcomes as new information becomes available. Albreiki et al. (2024), for example, apply a tree-augmented Naive Bayes model to healthcare incident-management factors, demonstrating how machine-learning-based Bayesian modelling can support healthcare decision-making.

The combination of machine learning and Bayesian reasoning becomes particularly valuable when resource allocation involves uncertainty and competing priorities. Topuz et al. (2024) demonstrate how Bayesian belief networks can be integrated with analytical and machine-learning techniques for early risk detection and healthcare decision support. McLachlan et al. (2024) similarly demonstrate the use of Bayesian network modelling in healthcare by combining expert knowledge, literature, and health statistics.

Resource allocation also involves an important ethical and explanatory dimension. A technically accurate AI model may still produce problematic recommendations if decision-makers cannot understand why resources are being allocated in a particular manner. Rueda et al. (2024) emphasize the importance of explainability and procedural fairness in AI-based medical resource allocation. This suggests that resource-allocation systems should provide not only predictions but also interpretable reasoning.

Causal Bayesian networks can strengthen this capability by allowing decision-makers to examine potential effects of changes within the system. Rather than asking only which patients or facilities are likely to require resources, causal analysis can consider how different allocation decisions may influence outcomes.

Uddandaraao and Mahajan (2023) provide an important methodological foundation by applying causal Bayesian networks and Double Machine Learning to counterfactual supply-chain capacity allocation. Their approach demonstrates how machine learning and causal reasoning can be combined to evaluate alternative allocation decisions.

This study therefore proposes an integrated machine-learning and causal Bayesian network framework for healthcare resource allocation. The framework seeks to combine prediction, probabilistic reasoning, causal analysis, and scenario evaluation to improve the allocation of scarce healthcare resources.

Healthcare resource allocation is a complex decision-making problem because available resources are rarely sufficient to satisfy every requirement simultaneously. Healthcare facilities must prioritize competing needs involving patients, departments, medical equipment, medicines, personnel, and emergency services. The allocation problem becomes even more challenging when demand is uncertain or when unexpected incidents disrupt normal operations.

The development of healthcare information systems has generated large amounts of operational and clinical data that can support resource planning. These data can include patient volumes, treatment requirements, facility utilization, incident records, equipment availability, staffing levels, and service capacity. Machine learning provides mechanisms for analysing these data and identifying patterns that may support resource-allocation decisions.

Bayesian network models are particularly suitable for healthcare because they can represent uncertain relationships among multiple variables. Instead of treating healthcare factors as independent, a Bayesian network can represent how changes in one variable may alter the probability of another outcome. Albreiki et al. (2024) demonstrate the use of a Bayesian learning structure for examining organizational factors associated with healthcare incident management.

Healthcare resource allocation also requires prediction. Before resources can be allocated efficiently, organizations need to estimate future requirements. Machine-learning models can analyse historical patterns and generate predictions about demand or risk. Topuz et al. (2024) demonstrate how Bayesian belief networks and analytical techniques can support early healthcare risk detection and decision-making.

McLachlan et al. (2024) provide another important example of Bayesian network modelling in healthcare. Their framework incorporates expert knowledge, published evidence, and national health statistics, demonstrating how multiple information sources can be integrated into healthcare Bayesian models.

However, prediction does not necessarily establish what action should be taken. Suppose a hospital is predicted to require additional resources. A predictive model may identify the expected requirement but may not determine whether increasing capacity, transferring resources, or changing allocation priorities would produce the best outcome. This creates a need for causal decision support.

Causal reasoning focuses on the potential consequences of interventions. In healthcare resource allocation, this can involve questions such as what may happen if additional equipment is provided to a facility, if capacity is increased, or if scarce resources are transferred from one location to another.

Rueda et al. (2024) further demonstrate that AI-based resource allocation must consider explainability and fairness. Allocation decisions can have significant consequences, making it important for decision-makers to understand the reasoning behind recommendations.

The counterfactual perspective is particularly relevant. Uddandaraao and Mahajan (2023) demonstrate how causal Bayesian networks and Double Machine Learning can be used to examine alternative capacity-allocation scenarios. Extending this logic to healthcare can enable organizations to compare possible allocation strategies before committing resources. The background of the study is therefore based on the integration of machine learning, Bayesian networks, causal reasoning, and healthcare resource allocation. Combining these approaches can create a decision-support system capable of predicting requirements while also evaluating the potential effects of alternative allocation strategies.

Machine Learning in Healthcare Decision-Making

Machine learning has become increasingly important in healthcare because it can analyse complex datasets and identify patterns that may support decision-making. Healthcare systems generate large volumes of information, and machine-learning models can use these data to predict risks, classify cases, and estimate future requirements.

Albreiki et al. (2024) provide a strong example by applying a tree-augmented Naive Bayes model to healthcare incident management. Their study demonstrates how Bayesian machine-learning structures can be used to examine relationships among healthcare organizational factors and support improvement decisions.

Kumaraswamy et al. (2024) also demonstrate the value of Bayesian belief networks in healthcare through their analysis of healthcare fraud. Although fraud detection is different from resource allocation, the study is relevant because it demonstrates how Bayesian network reasoning can provide interpretable analytical support within healthcare environments.

Bayesian Networks in Healthcare

Bayesian networks provide a graphical representation of probabilistic relationships between variables. They are useful when decision-makers must work with incomplete information or uncertain outcomes.

McLachlan et al. (2024) demonstrate how Bayesian networks can combine expert knowledge, published literature, and national health statistics to model healthcare outcomes. This approach is relevant to resource allocation because healthcare decisions often require information from multiple sources.

Topuz et al. (2024) similarly demonstrate the value of Bayesian belief network-based analytics for early risk detection. Their use of what-if analysis is particularly relevant because resource-allocation decisions often require evaluation of alternative conditions.

Al Nuairi et al. (2024) further demonstrate the application of data-driven Bayesian belief networks to healthcare-sector analysis. Such approaches reinforce the usefulness of Bayesian models for identifying relationships among healthcare variables.

Causal Bayesian Networks and Resource Allocation

A major advantage of causal Bayesian networks is their ability to support reasoning about interventions. Rather than simply estimating probabilities, causal models can provide a basis for evaluating how changes to selected variables may affect downstream outcomes.

Uddandaraao and Mahajan (2023) provide direct methodological support for this approach through their counterfactual supply-chain capacity-allocation framework. Their use of causal Bayesian networks alongside Double Machine Learning demonstrates how predictive learning can be connected to intervention analysis.

Applied to healthcare, this approach can allow decision-makers to compare different resource-allocation strategies. For example, a model could estimate the expected consequences of increasing capacity at one facility compared with reallocating existing resources from another facility.

Explainability and Fairness

Resource allocation is different from many conventional prediction tasks because recommendations can directly influence access to scarce healthcare services. Rueda et al. (2024) emphasize that accuracy alone is

insufficient for AI-based medical resource allocation and that explainability and procedural fairness should also be considered. This is important for causal Bayesian network systems because their graphical structures can provide a more transparent representation of relationships among variables. Decision-makers may therefore have greater ability to understand why a particular resource allocation is recommended.

Table 1. Literature Supporting the Framework

Main contribution	Relevance
Bayesian machine learning in healthcare incident management	Very strong
Bayesian network modelling in healthcare	Very strong
Bayesian analytics and healthcare risk detection	Very strong
Explainability and fairness in medical resource allocation	Very strong
Counterfactual causal resource allocation	Very strong
Bayesian healthcare decision support	Strong
Data-driven Bayesian healthcare modelling	Strong
Causal machine-learning methodology	Supporting
AI and healthcare innovation	Supporting

METHODS

This study proposes a conceptual framework integrating machine learning and causal Bayesian networks for healthcare resource allocation. The framework consists of data collection, machine-learning prediction, Bayesian network construction, causal analysis, scenario evaluation, and resource allocation.

Data Collection

The framework considers data relating to patient demand, healthcare facility capacity, resource availability, equipment utilization, staffing requirements, incident occurrence, and emergency conditions. Historical and real-time information can be incorporated where available.

Machine-Learning Analysis

Machine-learning models are applied to identify patterns and estimate future resource requirements. Variables associated with demand, utilization, facility capacity, and operational risk are analysed to generate predictions. The output may include predicted demand levels, resource shortages, facility risk scores, and expected utilization.

Bayesian Network Development

A Bayesian network is constructed to represent relationships among key healthcare variables. Nodes can include: a) Patient demand; b) Resource availability; c) Facility capacity; d) Equipment requirements; e) Operational incidents; f) Emergency demand; g) Staffing levels; h) Service availability. Relationships between these variables are represented using conditional probabilities. Evidence from healthcare data and expert knowledge can be used to estimate the network parameters, following approaches demonstrated in healthcare Bayesian modelling (McLachlan et al., 2024).

Causal Analysis

The causal component identifies variables that can be treated as interventions. Examples include increasing facility capacity, transferring equipment, increasing staffing, or reallocating available resources. The framework estimates how changing an intervention variable could influence an outcome such as service availability, shortage probability, or resource utilization.

Scenario and Counterfactual Analysis

Alternative scenarios are evaluated to determine potential consequences of different allocation strategies. This follows the counterfactual logic demonstrated by Uddandaraao and Mahajan (2023).

Table 2. Illustrative Allocation Scenarios

Scenario	Condition	Possible intervention	Expected objective
Baseline	Normal demand	Existing allocation	Establish reference outcome
High demand	Increased patient requirements	Increase resources	Reduce shortage risk
Capacity constraint	Facility operating near maximum	Expand or redistribute capacity	Improve service availability
Equipment shortage	Insufficient critical equipment	Transfer equipment	Address critical need
Emergency	Sudden increase in demand	Emergency allocation	Maintain continuity
Combined disruption	Multiple constraints	Integrated allocation	Improve resilience

The final recommendation is based on the predicted risk, estimated causal effect, resource availability, and expected outcome of each intervention.

RESULTS AND DISCUSSION

Results

The proposed framework demonstrates how machine learning and causal Bayesian networks can provide complementary capabilities for healthcare resource allocation. Machine learning provides the predictive component by identifying patterns associated with increasing demand, resource shortages, operational incidents, and facility constraints.

The Bayesian component provides a probabilistic representation of the healthcare system. This enables decision-makers to examine how evidence about one variable may change the estimated probability of other outcomes. For example, information about increasing patient demand could update the estimated probability of resource shortage.

The causal component provides an additional decision-making capability by examining potential interventions. Instead of simply identifying a facility as likely to experience resource pressure, the framework can evaluate whether increasing resources at that facility is expected to improve service availability.

Scenario analysis can then compare multiple interventions. For example, a healthcare organization could compare increasing resources at a high-demand facility with transferring resources from a lower-demand facility. The preferred strategy can be determined based on expected benefits and available resources.

The framework also supports compound conditions. A facility may simultaneously experience high demand, limited capacity, and equipment shortages. Evaluating these conditions jointly can provide a more realistic representation of healthcare resource requirements than analysing each factor independently.

Table 3. Expected Decision-Support Outputs

Analytical output	Decision implication
Predicted demand	Estimate future resource requirements
Shortage probability	Identify high-risk facilities
Facility capacity estimate	Prioritize capacity interventions
Causal intervention effect	Compare alternative actions
Counterfactual outcome	Assess potential results before implementation
Allocation priority	Determine where resources should be directed

Overall, the framework produces a transition from prediction to intervention. This means that the final analytical output is not simply a risk estimate but an evidence-based basis for deciding where and how resources should be allocated.

Discussion

The integration of machine learning and causal Bayesian networks provides a useful approach to healthcare resource allocation because the two methods address different aspects of the decision problem. Machine learning is effective for identifying patterns and generating predictions, while Bayesian networks provide probabilistic reasoning and causal structures for understanding relationships among healthcare variables.

The healthcare application demonstrated by Albreiki et al. (2024) supports the use of Bayesian machine-learning methods for examining organizational factors and improving healthcare incident management. This is important because resource allocation is often affected by operational incidents, and identifying relationships among incident-related factors can help organizations prioritize interventions.

McLachlan et al. (2024) further demonstrate that Bayesian networks can integrate different forms of knowledge, including expert knowledge, published evidence, and healthcare statistics. This is particularly valuable in resource allocation because healthcare decisions may involve incomplete information. A Bayesian framework allows uncertainty to be explicitly represented rather than ignored.

Topuz et al. (2024) provide further support for the use of Bayesian analytics for early risk detection and what-if analysis. What-if analysis is particularly relevant to resource allocation because managers frequently need to compare alternative decisions before implementation. The ability to estimate how system conditions may change under alternative scenarios can improve preparedness.

The causal dimension represents one of the most important contributions of the proposed framework. Prediction alone can identify a likely shortage but cannot necessarily determine the most effective response. Causal analysis allows the decision-maker to ask intervention-oriented questions. For example, if a facility is predicted to experience a shortage, the system can evaluate whether additional resources, capacity expansion, or redistribution would produce the greatest improvement.

Uddandarao and Mahajan (2023) provide a methodological basis for this type of counterfactual reasoning. Their application of causal Bayesian networks and Double Machine Learning to capacity allocation

demonstrates how predictive and causal methods can be combined to evaluate alternative allocation decisions. Explainability is also important. Rueda et al. (2024) demonstrate that AI-based medical resource allocation requires attention to explainability and procedural fairness. A healthcare resource-allocation model should therefore provide understandable reasons for its recommendations. Bayesian network structures can contribute to this objective because the relationships between variables can be represented graphically and examined by decision-makers.

The framework can also support more efficient resource utilization. When resources are limited, allocating the same amount to every facility may be inefficient because needs and risks differ. A data-driven causal system can identify differences in demand, capacity, and expected intervention effects, allowing resources to be prioritized where they are most needed.

However, implementation requires careful attention to data quality. Incomplete or biased healthcare data may produce inaccurate predictions or misleading causal relationships. Expert validation should therefore remain part of the modelling process. Human decision-makers should also retain oversight, particularly for high-impact allocation decisions.

Overall, the proposed framework provides a bridge between predictive healthcare analytics and strategic intervention. Its value lies in integrating machine learning, Bayesian reasoning, and causal analysis into a unified decision-support process. This can enable healthcare organizations to anticipate resource requirements, understand system dependencies, compare alternative strategies, and make more informed allocation decisions.

CONCLUSION

Machine learning and causal Bayesian networks provide a promising foundation for improving healthcare resource allocation under uncertainty. Machine learning can help identify demand patterns, predict resource requirements, and detect emerging risks, while Bayesian networks can represent complex relationships and uncertainty within healthcare systems. Causal reasoning adds the ability to examine how specific allocation decisions may influence healthcare outcomes, while scenario analysis allows alternative strategies to be compared before implementation. Together, these capabilities can help healthcare organizations identify critical needs, prioritize scarce resources, improve transparency in decision-making, and respond more effectively to changing operational conditions. The integrated approach can ultimately support more efficient, proactive, and evidence-based healthcare resource allocation.

REFERENCES

- Al Nuairi, M., et al. (2024). A data-driven Bayesian belief network model for exploring patient experience drivers in healthcare sector. *Annals of Operations Research*, 342(3), 1797–1817. <https://doi.org/10.1007/s10479-023-05437-9>
- Albreiki, S., Simsekler, M. C. E., Qazi, A., & Bouabid, A. (2024). Assessment of the organizational factors in incident management practices in healthcare: A tree augmented Naive Bayes model. *PLoS ONE*, 19(3), e0299485. <https://doi.org/10.1371/journal.pone.0299485>
- Kopparthi, G. S. (2022). The future of medicine: AI's role in healthcare innovation. *TPM–Testing, Psychometrics, Methodology in Applied Psychology*, 29(S1), 1–6.
- Kumaraswamy, N., Ekin, T., Park, C., Markey, M. K., Barner, J. C., & Rascati, K. (2024). Using a Bayesian belief network to detect healthcare fraud. *Expert Systems with Applications*, 238, 122241. <https://doi.org/10.1016/j.eswa.2023.122241>
- Li, B., Li, X., Tian, Z., Lu, X., & Kang, R. (2024). General power laws of the causalities in the causal Bayesian networks. *International Journal of General Systems*, 53. <https://doi.org/10.1080/03081079.2023.2234076>
- McLachlan, S., Daley, B. J., Saidi, S., Kyrimi, E., Dube, K., Grosan, C., Neil, M., Rose, L., & Fenton, N. E. (2024). Approach and method for Bayesian network modelling: A case study in pregnancy outcomes for England and Wales. *medRxiv*. <https://doi.org/10.1101/2024.01.06.24300925>
- Rueda, J., Rodríguez, J. D., Jounou, I. P., Hortal-Carmona, J., Ausín, T., & Rodríguez-Arias, D. (2024). “Just” accuracy? Procedural fairness demands explainability in AI-based medical resource allocations. *AI & Society*, 39, 1411–1422. <https://doi.org/10.1007/s00146-022-01614-9>
- Shiba, K., & Inoue, K. (2024). Harnessing causal forests for epidemiologic research: Key considerations. *American Journal of Epidemiology*, 193(6), 813–818. <https://doi.org/10.1093/aje/kwae003>
- Topuz, K., Davazdahemami, B., & Delen, D. (2024). A Bayesian belief network-based analytics methodology for early-stage risk detection of novel diseases. *Annals of Operations Research*, 341(1), 673–697. <https://doi.org/10.1007/s10479-023-05377-4>

Uddandaraao, D. P., & Mahajan, A. (2023). Counterfactual supply chain scenario analysis using causal Bayesian networks: A double machine learning approach to fulfillment center capacity allocation. *International Journal of Advances in Signal and Image Sciences*, 34–46.