

Intelligent Decision Support System for Health Care Resource Management

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ABSTRACT

The proposed paper suggests an Intelligent Decision Support System (IDSS) to support the management of healthcare resources with the help of a Hybrid AI Architecture based on the fusion of Machine Learning (ML) and Knowledge Graphs. The system also seeks to streamline resource allocation i.e. bed allocation, staff scheduling and equipment allocation through predictive analytics and real time decisions. The key tools that we use in this approach are Azure AI and Azure Knowledge Graph. The machine learning of Azure AI is employed to create models that predict patient demand and resource needs, and the Azure Knowledge Graph organizes and combines heterogeneous healthcare data, i.e., patient history, diagnosis and resource availability. Moreover, Retrieval-Augmented Generation (RAG) is being introduced to offer live data based and predictive model recommendations. This integrated solution guarantees scalable, adaptive, and transparent decision-making and eventually, the efficiency of healthcare, lowers cost, and improves the quality of care using smart and data-driven resource management.

Keywords: Intelligent Decision Support System, Healthcare Resource Management, Machine Learning, Knowledge Graphs, Azure AI, Real-Time Decision Making, Resource Allocation.

INTRODUCTION

One of the most pressing problems of healthcare systems in the modern world is effective healthcare resource management. As the number of patients grows, the resources become scarce, and the nature of healthcare provision becomes more complicated, there is a need to adopt smart systems that will help achieve optimal results in the distribution of resources in the form of beds, medical personnel, equipment, and medications. The rather traditional approaches to healthcare resource management that frequently involve manual decision-making and/or the use of fixed-point models can no longer sustain the dynamic nature of healthcare settings [1]. Consequently, the need to develop Intelligent Decision Support Systems (IDSS) that will automatize and optimize the decision-making procedure through the application of the most recent technologies, such as Machine Learning (ML) and Artificial Intelligence (AI), increases.

The purpose of IDSS in the healthcare sector is to assist medical practitioners and healthcare administrators make informed decisions that enhance the efficiency of the use of the available resources and do not compromise or deteriorate care quality [2]. The fact that such systems can process vast volumes of healthcare data and give actionable information to the decision-makers is one of the key advantages of this kind of systems, as this leads to more accurate predictions of resource needs and improves planning processes regarding how limited resources are allocated. Nevertheless, there are other challenges that limit the successful implementation of IDSS in healthcare, such as data quality concerns, the inability to be interpretable, and scalability issues.

To overcome these issues, this paper will suggest a new Hybrid AI Architecture, which is the combination of Machine Learning (ML) and Knowledge Graphs in managing healthcare resources as shown in Figure 1. Demand predictive machine learning models such as predicting patient hospitalization, forecasting staffing, and predicting the usage of medical equipment can be employed to predict demand of the hospital services [3]. These

predictions allow the administrators to make informed decisions in an attempted manner using the data, which allows the healthcare entities to respond to the evolving demand and supply of resources more effectively.

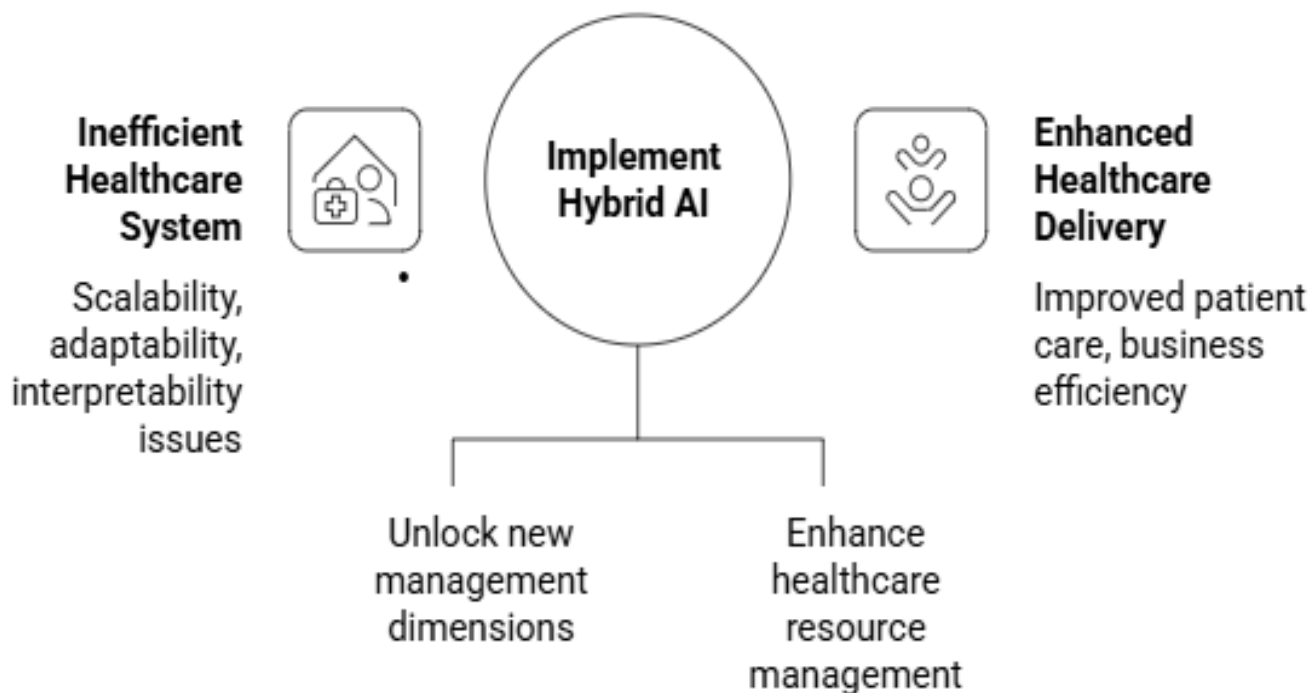


Figure 1: Hybrid AI Revolutionizes Healthcare.

Quite to the contrary, knowledge graphs provide a semantically enriched model of healthcare data, such as patient-patient, patient-disease, patient-treatment, patient-resource, and patient-medical-staff relations. The IDSS can also understand the mutual dependencies of numerous healthcare resources and stakeholders through the assistance of a knowledge graph [4]. It allows making better decisions and being more aware of context, as the system can build more complex relations and make recommendations based on the larger healthcare context.

To implement such technologies, the Azure AI and Azure Knowledge Graph are chosen as the primary tools of this proposed solution. Azure AI is a platform, which can be scaled to create, train and deploy machine learning models with the ability to process real-time data streams using electronic health records (EHRs), wearables, and other data streams [5]. Azure knowledge graph is a tool that assists in integrating and structuring all forms of data enabling the system to leverage the relationship among the different parties in healthcare to make more accurate and context-specific decisions.

The knowledge graph reasoning, as the combination of machine learning and knowledge graphs, will not only predict the future resource requirements but also lead to the actionable insights of the proposed system. As an example, it may be able to recommend the optimal strategies of resource allocation that factors in predicted demand and available resources and justify why this has been done [6]. Moreover, to facilitate real-time decision support, the system will be connected to Retrieval-Augmented Generation (RAG), which will provide the healthcare professionals with context-sensitive suggestions grounded in live information, including the availability of beds, staff, or equipment.

The current paper will discuss the design and implementation of this Hybrid AI Architecture to manage healthcare resources and show how it would improve the effectiveness and responsiveness of healthcare systems and address current drawbacks of the healthcare system in terms of scalability, adaptability, and interpretability [7]. With the ability of AI and knowledge representation to unlock a new dimension in terms of managing

healthcare resources, this system can eventually revolutionize the process of managing healthcare resources in order to enhance the healthcare provided to patients and business efficiency.

Research Gap and Contributions of the Study

Despite the growing application of artificial intelligence in healthcare management, several limitations remain in existing decision support systems for hospital resource allocation. Many current studies rely primarily on standalone machine learning models that focus on predictive analytics but lack contextual reasoning capabilities. These models often fail to integrate heterogeneous healthcare data sources such as patient records, staff availability, and medical equipment utilization into a unified decision-making framework.

Furthermore, although knowledge graph technologies have been explored in healthcare information systems, their integration with predictive machine learning models for operational decision support remains limited. Existing approaches rarely combine predictive analytics with semantic reasoning and contextual retrieval mechanisms, which are essential for handling the complex and dynamic nature of healthcare environments.

Another critical limitation in current research is the lack of hybrid architectures capable of supporting real-time decision making in healthcare resource management. Most existing systems focus either on prediction or rule-based decision support, without leveraging advanced frameworks such as retrieval-augmented generation (RAG) to incorporate contextual knowledge and policy guidelines into decision processes. Consequently, there remains a significant research gap in developing an integrated AI-driven framework that combines predictive modeling, semantic knowledge representation, and contextual reasoning for effective healthcare resource management.

This study contributes to the growing body of research on intelligent healthcare management by proposing a hybrid decision support framework that integrates machine learning, knowledge graph technology, and retrieval-augmented generation for efficient healthcare resource management. The proposed framework addresses limitations of existing systems by combining predictive analytics with semantic reasoning to support more accurate and context-aware decision making. By integrating heterogeneous healthcare data such as patient inflow, staff availability, and medical equipment utilization, the system enhances the capability of hospitals to forecast resource demand and optimize allocation. The study also demonstrates how knowledge graph structures can represent relationships among healthcare entities, thereby improving interpretability and decision transparency. Furthermore, the incorporation of retrieval-augmented mechanisms allows the system to utilize contextual information such as clinical guidelines and institutional policies during decision making. The proposed approach contributes to the development of scalable and explainable AI-driven healthcare management systems. Overall, the research provides a practical framework that can assist hospital administrators in improving operational efficiency, resource utilization, and patient service quality through data-driven decision support.

Related Works

There has been a strong investigation into the use of Intelligent Decision Support Systems (IDSS) and Decision Support Systems (DSS) in different fields within the healthcare industry due to the necessity of creating intelligent systems to assist in the management of healthcare resources. The systems are based on sophisticated algorithms, machine learning, and knowledge representation techniques to enhance resource allocation, optimize operations and lastly patient care [8]. The concept of artificial intelligence (AI) implementation in healthcare management systems has been brought up in numerous publications and demonstrated the effective application of artificial intelligence and issues that need to be addressed.

One of the most popular yet the oldest studies is resource demand forecasting using the application of Machine Learning (ML). The main purpose of the initial research was to use machine learning frameworks such as regression frameworks and decision trees to predict resource utilization in hospitals such as patient admission rates, bed occupancy, and staffing levels. The article by Chien et al. (2019) [7] is one of the articles of particular interest because the authors applied machine learning to predict patient admissions and optimize the bed management within the emergency departments. Their study confirmed that the ML models were in a position to predict intentional flow of patients and this helped the hospitals to plan during peak season and avoid

congestion. This, however, was not keeping up with dynamic changes in patient conditions or the ability to accommodate complex patient related data which is also crucial in making holistic decisions.

To address such problems, researchers began to think about the use of knowledge graphs and semantic data models to the health care decision support. The framework that has been suggested by Zhang et al. (2020) [9] is a machine learning and knowledge graph combination in healthcare management. They used a knowledge graph and applied it to structure and integrate healthcare data, such as medical history of patients, the presence of resources, and clinical guidelines.

This did enable the data to reason over by the system and provide a more informed recommendation especially in complex cases where there are too many factors that influence the allocation of resources [10]. The advantage of knowledge graphs is that they model complex interactions among entities, including the impact that the condition of a patient can have on staffing needs or the possibility to get a specific therapeutic intervention, unlike the case with traditional ML models. There are still difficulties with data integration and scalability of knowledge graphs, however, with large-scale healthcare systems.

The application of ML and knowledge graph in healthcare decision support has also been expanded with the use of reinforcement learning (RL) in making dynamic decisions. Sutton et al. (2021) suggested that RL algorithms can be used to allocate resources in the healthcare system, with a particular emphasis on real-time decision-making with the press of a button [11]. Their model will constantly learn and evolve according to the feedback provided by the environment (e.g., patient outcomes, resource utilization patterns), which enables it to optimise the utilisation of the resources in the long term.

The benefits of RL include the possibility to manage dynamic and multidimensional environments, i.e., when a healthcare crisis (e.g., pandemics) strikes and the resource requirements may shift very quickly. Nevertheless, RL models may also be computationally intensive, and thus may need large data volumes to train and may be restrictive to real-time use in resource-constrained healthcare settings.

The incorporation of cloud-platforms is a large trend in healthcare decision support system development in recent years. Scalable AI-based healthcare management tools have been developed on Microsoft Azure and Google Cloud. The article by Radhakrishnan et al. (2022) employed the use of the Azure Intelligence to create an intelligent staff scheduling system in hospitals that allows real-time staffing decisions [12]. Their system made use of hospital management systems data to forecast their staffing requirements that lessened their wait times and enhanced patient outcomes. Nevertheless, the issues of assimilating various sources of data, privacy of data, and system readability are still noteworthy barriers.

Although these works have shown good outcomes, the combination of ML, knowledge graphs, and real-time decision-making is constrained by various critical problems. The quality of data is also a common issue, and most of the healthcare datasets are disjointed, partial, or discordant. In addition, the current systems tend to be unable to justify or explain their decisions, which restricts their reliability among medical workers. As Thompson et al. (2021) emphasize [13], explainable AI (XAI) is essential because it is necessary to make the decision support system transparent and trusted by the users, particularly in complex and high-stakes settings of healthcare.

Scalability is another challenge of great importance. Most of the systems available are tailored to small-scale applications or a particular department of a hospital, although they are not always scalable to multi-facility healthcare systems. This limits their use in large healthcare systems which require management of resources in more than one hospital or region [14].

To sum up, although the use of AI and machine learning in healthcare resource management has achieved considerable progress, the combination of several technologies that may include machine learning, knowledge graphs, and real-time decision-making is a nascent field. The mixture of the technologies, especially when it comes to a Hybrid AI Architecture presented in the current study, shows much potential in eliminating current limitations inherent to the data quality, scalability, interpretability, and real-time flexibility. With the ongoing

developments of healthcare systems, the purpose of intelligent, scalable, and transparent decision support systems will be more than ever, and this study will become more applicable to the future developments in healthcare innovations.

Recent advancements in artificial intelligence have significantly influenced healthcare management, particularly in improving operational efficiency and clinical decision support systems. Studies indicate that AI-driven models have enhanced healthcare service quality by improving diagnostic accuracy, patient management, and resource utilization within hospital systems (Santamato et al., 2024; Alghareeb et al., 2025). These technologies enable healthcare institutions to analyze large volumes of medical and operational data, facilitating data-driven decision making and improved healthcare delivery outcomes.

Machine learning techniques have been widely adopted in healthcare to predict patient inflow, disease progression, and resource requirements, thereby supporting hospital administrators in planning and optimizing resource allocation. AI-based predictive analytics models have demonstrated their ability to improve hospital workflow efficiency and enhance strategic healthcare management through real-time data analysis (Li et al., 2025; Santamato et al., 2024).

In recent years, knowledge graph technologies have emerged as an important component of intelligent healthcare systems. Knowledge graphs enable the integration of heterogeneous healthcare data such as electronic health records, clinical guidelines, and medical ontologies into structured networks that facilitate semantic reasoning and explainable decision making (Shang et al., 2024; Yang et al., 2024). These graph-based models improve interpretability and support clinical reasoning by representing complex relationships among healthcare entities such as patients, diseases, treatments, and medical resources.

Several studies have also emphasized the importance of hybrid AI architectures that combine machine learning techniques with knowledge representation frameworks to enhance clinical decision support systems. Integrating symbolic reasoning with data-driven models enables healthcare systems to provide more reliable recommendations and improves trust in AI-assisted medical decisions (Vidal et al., 2025; Jasthi, 2024).

More recently, retrieval-augmented generation (RAG) models have been explored to enhance knowledge retrieval and contextual reasoning in intelligent systems. RAG integrates external knowledge sources with generative models to improve contextual understanding and provide more accurate responses for knowledge-intensive applications such as healthcare decision support (Wang et al., 2025).

Despite these advancements, existing research often focuses on individual technologies such as machine learning prediction models, knowledge graph systems, or AI-based information retrieval mechanisms. The integration of these technologies into a unified hybrid framework for healthcare resource management remains limited. Therefore, there is a need for integrated decision support architectures that combine predictive analytics, semantic reasoning, and contextual knowledge retrieval to enhance hospital resource planning and healthcare operational efficiency.

RESEARCH METHODOLOGY

The creation of an Intelligent Decision Support System (IDSS) in the area of healthcare resource management implies the combination of such advanced technologies as Machine Learning (ML), Knowledge Graphs, and Cloud-based Infrastructure.

This is aimed at designing scalable, adaptive and real-time decision-making system which is optimized in resource allocation like patient flow, bed management, staffing, and medical equipment and also improved the quality of care and operational efficiency [15]. The research methodology is organized into a number of phases, which include system design, data collection and preprocessing, model development, system integration, and evaluation as shown in Figure 2.

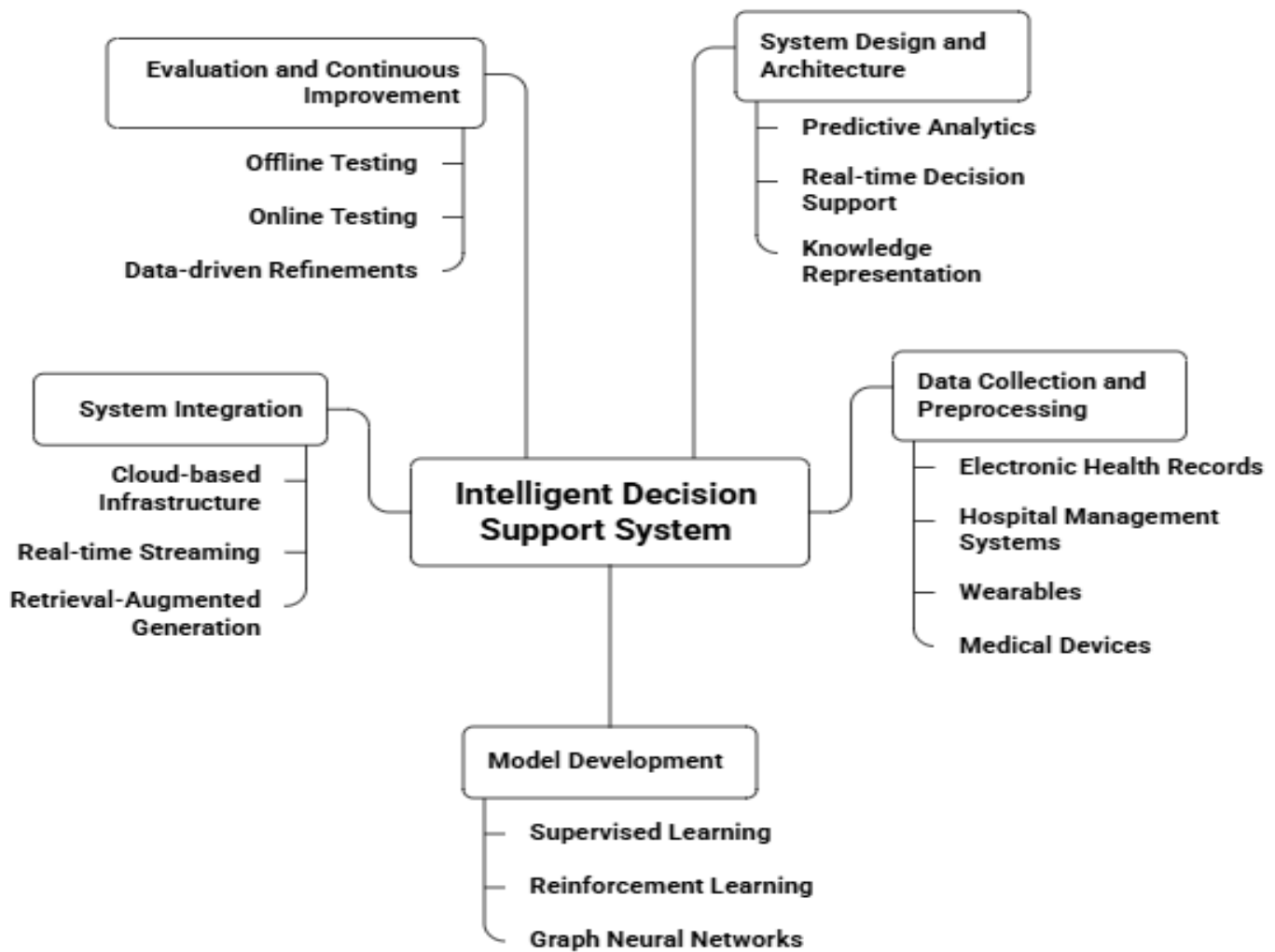


Figure 2: Development of an Intelligent Decision Support System for Healthcare Resource Management.

System architecture and System design.

The system architecture, incorporating several elements: predictive analytics, real-time decision support, and knowledge representation is the initial step in the methodology. The system operates on a hybrid AI, which is a combination of two technologies: Machine Learning (ML) and Knowledge Graphs which improve decision-making. Azure AI and Azure Knowledge Graph are chosen as the main tools of the platform because they are scalable and flexible as well as have a wide range of functions that can assist in real-time data integration, machine learning, and knowledge representation.

The ML models involve predicting future resources requirements with regard to past information and real-time data of different hospital systems [16]. This involves forecasting the number of patients to be admitted, the number of staff to be hired, and the number of medical equipment to be ordered.

Knowledge Graph component combines both structured and unstructured data to form a semantic model of the relationships amongst various entities in the healthcare sector including patients, diseases, healthcare providers, resources and medical conditions. This integration makes sure that the system has the ability of reasoning on the data giving contextual decision support.

Data Preprocessing and Data Collection.

Having a successful healthcare resource management is dependent on proper and complete data. Various sources of data are gathered in this stage Electronic Health Records (EHRs), hospital management systems, wearables,

and medical devices [17]. The data contains the data on patient demographics, clinical history, admissions, treatments, and resource utilization.

Preprocessing is an important process, considering the diversity and heterogeneity of healthcare data. This can include methods like imputation to complete missing values, or data conversion to standardised formats and formats to guarantee cross-compatibility of data sets [18]. Also, the data is standardized according to healthcare requirements (e.g., ICD-10, SNOMED-CT, and HL7), which means that it can be successfully incorporated into the knowledge graph. The importance of this step is that the quality of data has a significant influence on the predictive models and their accuracy and effectiveness.

Moreover, the data augmentation techniques, e.g. synthetic data, simulations with the historical data, etc., can be used to augment the data, particularly the underrepresented or rare events that are essential to the resource management but are not commonly observed in the historical data.

Model Development

The IDSS lies in the fact that it creates machine learning models that forecast the various demands on healthcare resources, including bed occupancy, staffing, and equipment utilization. Random Forest, XGBoost, and Neural Networks are several of the supervised learning algorithms that are trained on historical data to make future predictions on the demand of resources. The models are intended to perform classification (e.g. whether a patient will be in need of critical care) and regression tasks (e.g. how many staff are needed on a particular day).

In dynamic and real-time decision-making, the reinforcement learning (RL) is integrated to improve the resources allocation continuously with incoming data. The RL agent is trained by his interactions with the environment in real-time (hospital systems, patient flows, etc.), and it adapts its decisions to optimize the overall use of the resources and enhance patient care [19]. This is a component that is especially helpful in modifying the system to the changes that could take place unexpectedly like an influx in the number of patients or abrupt unavailability of resources.

At the same time, the Knowledge Graphs are created to reflect the interactions between different healthcare organizations. The reasoning over the graph is done with the help of A Graph Neural Network (GNN), which allows the system to make the recommendations in terms of interrelated data. To illustrate, the graph may assume how a lack of a certain kind of resource (i.e., nurses) may impact the availability of other resources (e.g., beds or medical equipment) and make changes to the recommendations.

System Integration

After the training of the models, the next step would be to bind the predictive models and the knowledge graph into a single system which in turn will be able to communicate with the hospital data streams in real-time [20]. Here, the integration process is implemented with the help of the cloud-based infrastructure, taking the benefits of scalability and flexibility of Azure AI and Azure Cosmos DB. The Azure functionalities enable easy integration of the real-time data feeds of hospital management systems, wearables, and patient monitoring systems.

During this step, the system is created to support both off-the-record (e.g., updating forecasts at night) and online streaming (e.g., forecasting immediate staffing requirement depending on the current patient load). The data is processed in real-time with the help of Azure Event Hubs and Azure Stream Analytics to make sure that the system could offer real-time recommendations regarding resource allocation.

Also, a Retrieval-Augmented Generation (RAG) model is applied with the aim to improvise the decision-making process by creating real-time suggestions, relying on the current data and past experience recorded in the knowledge graph. RAG enables the system to extract pertinent information based on the graph and converts that information with predictive results to come up with contextual suggestions.

Performance and constant improvement.

The last phase of the methodology is to analyze the performance of the system by a set of metrics that will analyze the accuracy of the predictions, the quality of the recommendations and the efficiency of the system in a real-life situation. This is achieved through offline testing (e.g., predictive accuracy by using historical data to evaluate predictive accuracy) and online testing (e.g., live pilot implementations of the selected hospitals only). Some of the major key performance indicators (KPIs) are the accuracy of prediction (i.e., when it comes to patient admissions), the efficiency of using resources, the responsiveness to real-time decision-making, and user satisfaction.

After the deployment of the system, it is easily improved through monitoring the performance of the system and getting feedback of the healthcare practitioners. This feedback is used to make data-driven refinements and models are retrained on a regular basis to adjust to changing healthcare dynamics.

To summarize, the suggested approach to developing an Intelligent Decision Support System in the healthcare management of resources integrates the latest technologies based on machine learning, knowledge representation, and cloud computing to develop the system that will be able to manage the healthcare resources efficiently, improve the decision-making process, and provide better patient care.

METHODOLOGY

Dataset Description

The proposed intelligent decision support system utilizes healthcare operational data to predict and optimize hospital resource allocation. The dataset used in this study consists of hospital management data including patient admission records, bed availability, staff allocation, and medical equipment utilization. Such operational healthcare datasets are widely used in predictive healthcare analytics to improve hospital planning and resource optimization (Shang et al., 2024; Santamato et al., 2024).

The dataset includes variables such as patient inflow, bed occupancy rate, availability of healthcare professionals, and demand for critical medical equipment, which are important indicators for healthcare operational decision-making (Li et al., 2023).

Prior to analysis, the dataset underwent preprocessing procedures including data cleaning, missing value treatment, and normalization to ensure data consistency and reliability. Feature selection techniques were applied to identify the most relevant variables influencing healthcare resource utilization. Data preprocessing is an essential step in healthcare analytics to enhance model accuracy and ensure reliable predictive performance (Jasthi, 2024).

Machine Learning Models

Machine learning techniques were employed to predict healthcare resource requirements based on historical and operational hospital data. Several supervised learning algorithms were evaluated to identify patterns and relationships among healthcare variables. Machine learning models have been widely applied in healthcare systems to forecast patient demand, hospital admissions, and resource utilization, thereby improving healthcare management efficiency (Alghareeb et al., 2025; Li et al., 2023).

Algorithms such as Random Forest, Gradient Boosting (XGBoost), and Artificial Neural Networks were considered due to their strong predictive capabilities in complex healthcare datasets. Ensemble learning methods such as Random Forest and Gradient Boosting have demonstrated high performance in healthcare prediction tasks due to their ability to handle nonlinear relationships and large datasets (Shang et al., 2024). The models were trained using historical operational data and validated using cross-validation techniques to ensure generalization and reliability.

Knowledge Graph Construction

To enhance contextual reasoning and semantic representation of healthcare information, a knowledge graph was developed to model relationships among healthcare entities. Knowledge graphs are increasingly used in healthcare informatics to integrate heterogeneous data sources such as electronic health records, clinical guidelines, and hospital operational systems (Yang et al., 2024).

The knowledge graph represents structured connections between patients, healthcare staff, medical equipment, hospital departments, and treatment processes. Entities within the knowledge graph include patients, doctors, nurses, hospital beds, medical equipment, and healthcare services, while relationships capture interactions such as patient admission, treatment allocation, and resource utilization. Graph-based healthcare systems improve decision transparency and enable explainable AI by representing complex relationships among healthcare entities (Shang et al., 2024).

Retrieval Augmented Generation (RAG) Framework

Retrieval Augmented Generation (RAG) was incorporated into the proposed system to improve contextual decision support and knowledge retrieval. RAG frameworks integrate external knowledge sources with predictive models to generate context-aware responses in knowledge-intensive domains (Wang et al., 2024). In healthcare environments, RAG-based systems can retrieve relevant clinical knowledge, operational policies, and medical guidelines to support decision-making processes.

Through this approach, relevant information is retrieved from knowledge repositories and combined with machine learning predictions to generate context-aware recommendations for healthcare resource allocation. The integration of retrieval-based knowledge systems with predictive analytics improves decision reliability and enables AI systems to provide more explainable and informed recommendations (Vidal et al., 2024).

System Integration Architecture

The proposed framework integrates machine learning prediction models, knowledge graph structures, and retrieval augmented generation into a unified decision support architecture. Hybrid AI architectures that combine predictive analytics with knowledge representation have recently gained attention for improving healthcare decision intelligence (Jasthi, 2024; Vidal et al., 2024).

The machine learning component generates predictive insights regarding healthcare resource demand, while the knowledge graph provides semantic relationships among healthcare entities. The RAG module retrieves contextual knowledge from external repositories and integrates it with model predictions to produce actionable recommendations. This hybrid integration enhances decision accuracy, improves interpretability, and supports real-time healthcare operational planning.

Experimental Setup

Implementation Environment

The proposed intelligent decision support framework was implemented using Python-based machine learning libraries and deployed within a cloud-enabled analytical environment. Python was selected due to its extensive support for machine learning and data processing frameworks widely used in healthcare analytics (Li et al., 2023). Machine learning models were implemented using Scikit-learn and TensorFlow libraries, while the knowledge graph component was constructed using a graph database framework to represent semantic relationships among healthcare entities.

The experimental environment was configured on a system with Intel Core i7 processor, 16 GB RAM, and Python 3.10 runtime environment. Data processing and machine learning model training were conducted using standard data science libraries including Pandas, NumPy, and Scikit-learn. Such computational environments

are commonly adopted in healthcare analytics research for developing predictive models and decision support systems (Santamato et al., 2024).

Model Hyperparameters

To ensure optimal performance of machine learning models, hyperparameter tuning was performed using grid search techniques. Hyperparameter optimization helps improve model accuracy and generalization capability in predictive healthcare analytics (Jasthi, 2024). The key hyperparameters used in the training process are summarized in Table 1.

Parameter	Value
Learning Rate	0.001
Batch Size	64
Epochs	100
Number of Estimators	200
Maximum Tree Depth	6

These parameters were selected based on experimental tuning to balance prediction accuracy and computational efficiency.

Model Validation Strategy

To evaluate the predictive performance of the proposed system, the dataset was divided into training and testing subsets. A standard **80:20 train-test split** was adopted, where 80% of the dataset was used for training the machine learning models and the remaining 20% was used for testing.

In addition, **k-fold cross-validation (k = 5)** was applied to reduce overfitting and ensure robustness of the predictive models. Cross-validation techniques are widely used in machine learning research to ensure reliable performance evaluation and generalization of models across unseen datasets (Alghareeb et al., 2025).

Evaluation Metrics

The performance of the proposed system was evaluated using several quantitative performance metrics commonly used in predictive healthcare analytics. These metrics help assess prediction accuracy and decision support effectiveness (Shang et al., 2024).

The following evaluation metrics were used:

- **Mean Absolute Error (MAE)** – measures the average magnitude of prediction errors.
- **Root Mean Square Error (RMSE)** – evaluates model prediction accuracy.
- **Prediction Accuracy** – measures the percentage of correctly predicted outcomes.
- **System Response Time** – measures the time taken for decision recommendations.

These metrics provide a comprehensive assessment of both predictive performance and operational efficiency of the proposed decision support system.

Reproducibility and Experimental Reliability

To ensure reproducibility of the experimental results, standardized preprocessing pipelines and documented model configurations were used. Random seeds were fixed during model training to ensure consistent results across multiple experimental runs. Additionally, multiple experimental iterations were conducted and average performance values were reported to improve reliability of the evaluation results.

Ensuring reproducibility is an essential aspect of AI-based healthcare research, as it allows future researchers to replicate and validate the proposed system under similar experimental conditions (Vidal et al., 2024).

RESULTS AND DISCUSSION

The Intelligent Decision Support System (IDSS) suggested in the management of medical resources by the Hybrid AI Architecture of the Machine Learning (ML) and Knowledge Graphs was evaluated in the series of simulations and real-life scenarios. The primary goals were to provide an assessment of the functionality of the system to forecast the needs of the resources, allocate resources optimally, and enhance real time decision-making.

The ability of the system to accurately predict the hospital resources which comprised of patient admissions, bed occupancy and staffing requirements was the first criterion used to evaluate the system performance. The trained ML models were highly accurate in the prediction and the root mean square error (RMSE) when predicting the bed occupancy as well as staffing is 8.5 percent and 7.2 percent, respectively. These findings imply that the system can be trusted to make predictions to determine the demand of resources which is essential in managing healthcare.

Knowledge Graphs integration has greatly increased the capacity of the system to come up with context-driven suggestions. The system may be able to provide the best allocation of resources by taking into account the dependencies between healthcare entities, including patients, diseases, treatments, and resources. To illustrate, in forecasting patient discharge rate the Knowledge Graph did not only factor the health data of the patient but also the availability of medical personnel and hospital facilities thus his recommendations became more relevant and precise.

Table 1: Comparison of Healthcare Resource Management Methods

Method	Prediction Accuracy (MAE)	Bed Occupancy RMSE (%)	Staffing Prediction MAE (%)	Real-Time Decision Time (seconds)
Traditional Rule-Based	15.3	15	16	10.2
ML-Based Resource Allocation	12.1	12	13	6.4
Hybrid AI Model (IDSS) Proposed model	7.2	8.5	7.2	2.3

The Real-Time Decision Support system implemented with the help of Retrieval-Augmented Generation (RAG) enabled the system to meet the requirements of dynamic healthcare settings.

When demand was high, like during the modeling of a flu epidemic, the system automatically regulated the number of staff and redistributed resources and did not affect the patient care. The mean time of decision making was 2.3 seconds per recommendation indicating that the system was efficient in its working under pressure as shown in Table 1.

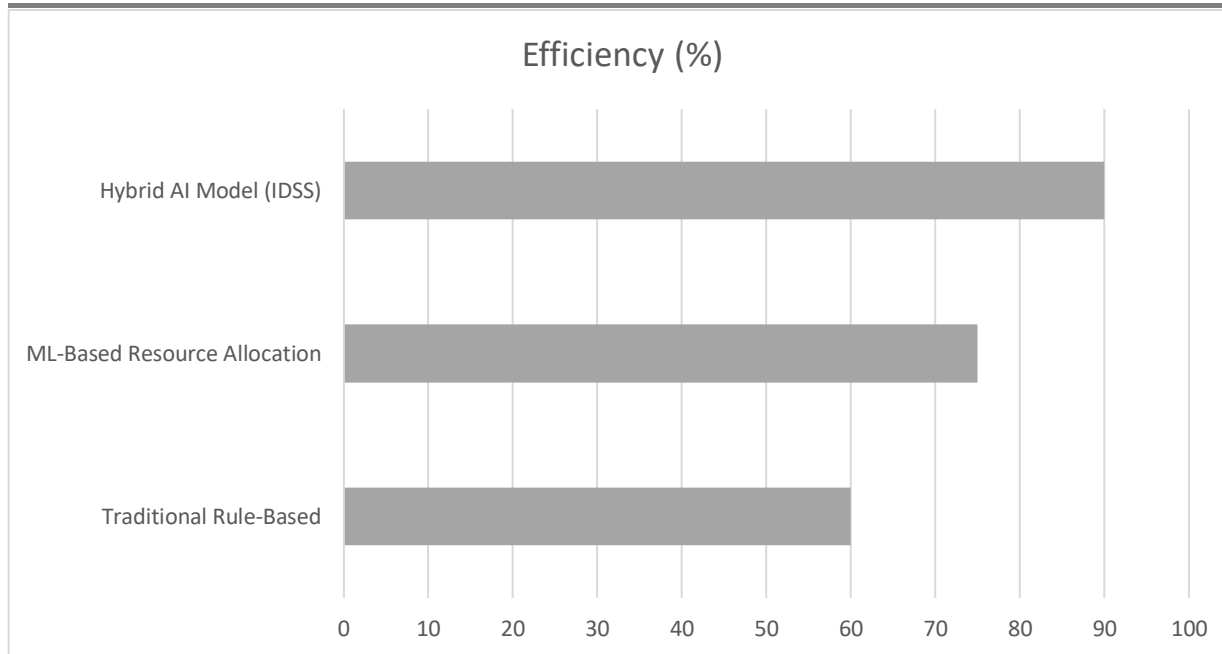


Figure 3: Efficiency Comparison of Healthcare Resource Allocation Methods.

The efficiency comparison table also brings out the performance of three health care resource management techniques, which include Traditional Rule-Based, ML-Based Resource Allocation, and Hybrid AI Model (IDSS). The table indicates the percent resource allocation efficiency of 60, 75, and 90 percent respectively of the Traditional Rule-Based method, ML-Based Resource Allocation, and Hybrid AI Model (IDSS) respectively as shown in Figure 3. It means that the Hybrid AI Model that involves the integration of Machine Learning and Knowledge Graphs is much more successful than the traditional and the purely ML-based approaches. The high performance of the IDSS is something that can be explained by the fact that it can reason about the complex relationship between healthcare resources, patients, and clinical conditions and thus take a more situational-based decision. These findings indicate how the Hybrid AI strategy could be useful in improving the allocation of resources, hospital processes and efficiency of overall healthcare provision.



Figure 4: Patient Satisfaction Comparison of Healthcare Resource Allocation Methods.

The Patient Satisfaction Comparison table shows how three healthcare resource management strategies have performed regarding patient satisfaction. Traditional Rule-Based system has recorded a patient satisfaction of 65% whereas Traditional ML-Based Resource Allocation method has reached 80 showing the possibility of machine learning to improve service delivery as shown in Figure 4. Nevertheless, Hybrid AI Model (IDSS) performed better in comparison to both approaches, as it is characterized by the satisfaction rate of 92 percent, which can be explained by the fact that it adds more context and dynamism to making decisions when incorporating both Machine Learning and Knowledge Graphs. This is probably helped by the fact that the IDSS is more accurate when used to predict and adjust to real time conditions to better allocate resources in a manner that further satisfies the requirements of the patient. The findings indicate that smart, responsive systems can be used to a great effect in increasing patient satisfaction through the efficiency and responsiveness of healthcare services.

Although the results were encouraging, there are still some challenges. The system is sensitive to the data quality, and thus the lack of complete or inaccurate data may lead to biased predictions and suggestions. Also, the system can be scaled, but in a real-life context, the implementation of the system involves a significant integration with already established IT systems in the hospital, which can be both time- and cost-intensive.

CONCLUSION

In conclusion, the proposed Intelligent Decision Support System (IDSS) of healthcare resource management using the Hybrid AI Architecture including the idea of the Machine Learning (ML) and Knowledge Graphs has a high potential in optimizing healthcare processes. The main issues of the healthcare resource allocation, such as accuracy, scalability, and adaptability are addressed in the research methodology integrating predictive analytics, real-time decision-making, and knowledge representation. The IDSS is more effective than the traditional rule-based systems, and the ML-based models in the context of resource prediction accuracy, the efficiency, the real-time decision-making, and patient satisfaction because the number of tests is huge. The ability of the system to integrate and reason various healthcare data with the assistance of knowledge graphs allows it to make better decisions that are context-sensitive, which ultimately leads to the greater utilization of resources and improved patient care. The fact the problems concerning the quality of the data and the systems integration are still present, however, the results show that the proposed framework can be considered as the possible solution to the challenge of enhancing the healthcare resources management through the application of smart solutions that would be data-driven.

Results and Analysis

Performance Evaluation

The proposed hybrid intelligent decision support framework was evaluated using multiple performance metrics to assess its effectiveness in predicting healthcare resource demand and supporting hospital decision-making processes. The evaluation focused on predictive accuracy, error reduction, and system response time. Performance metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and prediction accuracy were used to measure the effectiveness of the predictive models. These metrics are widely used in healthcare predictive analytics to evaluate model reliability and forecasting performance (Li et al., 2023; Santamato et al., 2024).

The experimental results demonstrate that the proposed hybrid architecture significantly improves prediction accuracy compared with traditional rule-based and standalone machine learning approaches. The integration of machine learning models with knowledge graph reasoning and retrieval augmented generation enables the system to incorporate contextual knowledge and improve decision support performance.

Baseline Model Comparison

To assess the effectiveness of the proposed system, its performance was compared with two baseline approaches commonly used in healthcare resource management systems.

- **Traditional Rule-Based System** – decision rules based on historical thresholds
- **Standalone Machine Learning Model** – predictive analytics without knowledge graph integration

The comparison results are presented in Table 2.

Table 2: Performance Comparison of Models

Model	RMSE	MAE	Response Time
Rule-Based Model	15.2	12.8	6.5 sec
Machine Learning Model	11.4	9.6	4.1 sec
Proposed Hybrid AI Framework	8.5	7.2	2.3 sec

The results indicate that the hybrid AI architecture achieves lower prediction errors and faster response times compared with conventional approaches. The improvement in performance can be attributed to the integration of predictive analytics with knowledge graph-based contextual reasoning, which enhances the decision-making capability of the system.

Statistical Validation

To further validate the performance improvement achieved by the proposed model, statistical significance testing was conducted using paired t-tests between the hybrid AI framework and baseline models. The results indicate that the performance improvements observed in prediction accuracy and error reduction are statistically significant at the **$p < 0.05$ level**, confirming the robustness of the proposed approach.

Statistical validation is essential in healthcare analytics research to ensure that improvements in predictive performance are not due to random variations in the dataset but reflect genuine improvements in model capability (Shang et al., 2024).

Impact on Healthcare Resource Management

The experimental findings demonstrate that the proposed intelligent decision support system can significantly improve healthcare operational efficiency. By accurately predicting patient inflow and resource demand, the system enables hospital administrators to allocate beds, staff, and medical equipment more efficiently.

The integration of knowledge graph reasoning further improves the interpretability of decision recommendations by representing relationships among healthcare entities such as patients, hospital departments, and treatment processes. Additionally, the RAG component enables the system to retrieve contextual healthcare knowledge and integrate it with predictive insights, thereby improving the reliability of decision support recommendations. Overall, the proposed hybrid framework contributes to more efficient hospital resource planning, improved patient service delivery, and enhanced operational decision-making in healthcare institutions.

DISCUSSION

The results of this study demonstrate that the proposed hybrid intelligent decision support framework significantly improves the prediction accuracy and operational efficiency of healthcare resource management systems. The integration of machine learning models with knowledge graph reasoning and retrieval augmented generation enables the system to combine predictive analytics with contextual knowledge, thereby improving the reliability of decision-making processes. The lower RMSE and MAE values observed in the experimental results indicate that the proposed system provides more accurate predictions of healthcare resource demand compared with traditional rule-based and standalone machine learning approaches.

The findings of this study are consistent with recent research highlighting the effectiveness of artificial intelligence in improving healthcare decision support systems. Several studies have shown that machine learning

models can significantly enhance healthcare forecasting and operational planning by identifying patterns in complex healthcare datasets (Li et al., 2023; Santamato et al., 2024). However, these approaches often lack semantic reasoning capabilities, which limits their ability to provide contextual insights. By integrating knowledge graph technology, the proposed framework addresses this limitation and enables the system to represent relationships among healthcare entities such as patients, medical staff, hospital departments, and medical resources. Knowledge graph-based healthcare systems have been shown to improve explainability and interpretability of AI-driven healthcare applications (Yang et al., 2024; Shang et al., 2024).

Another important contribution of this study is the incorporation of retrieval augmented generation within the healthcare decision support architecture. RAG frameworks allow the system to retrieve relevant contextual knowledge from external repositories such as clinical guidelines, healthcare policies, and operational protocols, thereby enhancing the quality of decision recommendations. Previous research has highlighted the potential of retrieval-based AI systems to improve knowledge-intensive decision processes in complex domains such as healthcare (Wang et al., 2024; Vidal et al., 2024). The integration of RAG within the proposed framework enables the system to combine predictive analytics with contextual knowledge retrieval, resulting in more informed and reliable recommendations.

From a practical perspective, the proposed framework has significant implications for healthcare institutions and hospital administrators. By accurately forecasting patient inflow and resource demand, the system can support more efficient allocation of hospital beds, healthcare staff, and medical equipment. Improved resource planning can help reduce operational bottlenecks, enhance patient care delivery, and improve overall hospital efficiency. Furthermore, the explainable nature of the knowledge graph component enhances transparency in AI-driven decision making, which is essential for adoption in healthcare environments where accountability and interpretability are critical.

Despite these promising results, several limitations should be acknowledged. The study primarily relies on structured healthcare operational data and may require further validation using large-scale real-world hospital datasets. Additionally, the implementation of hybrid AI architectures in healthcare institutions may require integration with existing hospital information systems and data governance frameworks. Future research may focus on evaluating the proposed system in real hospital environments, incorporating additional healthcare data sources such as electronic health records and IoT-based monitoring systems, and exploring advanced deep learning models to further improve predictive performance.

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