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SPECIAL FOCUS PAPER

Explainable AI-Based Online Decision-Support System for Healthcare Supply Chain Risk Management

Ahmad Shaheen[1] (✉), Ikechukwu Torti[2], Sapna Bansal[3]

[1]Arab Academy for Science, Technology and Maritime Transport, Alexandria, Egypt

[2]Rushford Business School, Lucerne, Switzerland

[3]Shri Ram College of Commerce, University of Delhi, New Delhi, India

ahmad.yahya.shaheen@aast.edu

ABSTRACT

Disruptions in healthcare supply chains pose a risk to the availability of essential medical supplies and the sustainability of patient care. Although artificial intelligence (AI) has been employed in the management of supply chain risks, the lack of transparency of many of these approaches has restricted the adoption of such tools by healthcare procurement decision-makers. This paper will follow a design science research paradigm by introducing the conceptual design and descriptive assessment of an explainable AI-based online decision-support system in evaluating health care supply chain risks. The system incorporates the variables of supplier dependability, lead-time inconsistency, demand uncertainty, and the importance of medical supplies, which are integrated into an interpretable AI framework for real-time decision support. Risk factors and model outputs are used to provide understandable insights, fostering explainability and enhancing trust and ease of use in hospital procurement. A descriptive evaluation is undertaken using simulated healthcare supply chain scenarios to evaluate the functionality, interpretability, and decision-making influence of the system. The findings indicate the system can recognize and explain the factors of high-risk supply situations and can assist in the undertaking of proactive risk mitigation strategies. This study demonstrates how the operational reliability and resilience of supply chains in health care can be enhanced by integrating explainable AI with online decision-support systems.

KEYWORDS

artificial intelligence (AI), healthcare supply chain, decision-support systems, supply chain risk assessment, hospital procurement, digital health systems

1 INTRODUCTION

Healthcare is a basic element of the national economy, and it is vital in ensuring the health and well-being of the populace [1]. Nevertheless, global disruptions, such as pandemics and geopolitical conflicts, as well as climate change that may lead to serious delays, stockouts, and inefficiencies in the delivery of critical medical products, often pose a significant threat to the quality of medical supply chains [2].

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These structural weaknesses have led to repeated drug shortages and logistical breakdowns costing medical institutions millions of dollars every year and directly diminishing patient safety and clinical outcomes [2].

Hospital settings are dynamic and present specific threats, and therefore, there should be an active risk management approach that employs communication and setting of the context, risk assessment, and continuous monitoring [3]. The healthcare supply chain is a complex organization in which inefficient operation may have a direct impact on patient well-being and facility output, and supply chain risk management has become a more critical aspect to reduce supply chain variability in terms of time and expense [4].

These sophisticated algorithms are black-boxed in nature, which implies that they cannot be used to extract the logic behind them [5]. As a result, the non-interpretability of black-box models may create a distrusting attitude toward healthcare professionals and prevent the adoption of potentially useful artificial intelligence (AI) solutions [5]. Also, regulatory authorities are becoming stricter on what is known as an explanation of automated decisions as a way of compliance and accountability towards ethics [6].

The integration of AI into healthcare supply chains has garnered significant attention, yet existing literature predominantly emphasizes sustainable development and logistics optimization while overlooking the critical need for explainable decision-support frameworks in risk management. The fact that the stakeholders of the healthcare supply chain community tend to be reluctant to adopt AI techniques, which cannot be interpreted clearly, is especially problematic [7].

In this paper, the gaps are addressed through the conceptual design and descriptive assessment of an explainable AI-based web-based decision-support system in healthcare supply chain risk management. The paper takes a design science research approach as opposed to an empirically deployed system, thus making a contribution in the form of a theoretically grounded framework and prototype architecture that should be used as a guide towards implementation. The suggested system will integrate healthcare-related risk variables, such as supplier reliability, lead-time variability, demand variability, inventory sensitivity, and external disruption vulnerability, into an organized, AI-intermediated risk assessment system. The article contributes in three different ways. To start with, it builds a conceptual framework that effectively consolidates the key dimensions of supply chain risk addressed to operations in a hospital. Second, it suggests a demonstrably explainable system architecture of AI that incorporates risk assessment and interpretability into a common decision-support system. Third, it gives a descriptive analysis of the suggested system based on the scenarios of the healthcare supply chain, which illustrate its logical consistency and operational topicality as a conceptual artifact.

2 LITERATURE REVIEW

The healthcare industry, as one of the pillars of the national economy, plays a vital role in sustaining the health and well-being of the population, but it is incredibly sensitive to challenges that have the potential to threaten patient safety and cause disruptions in the work of the system [1]. The recent world crisis (such as the COVID-19 pandemic) revealed the inefficiency of such systems, showing how the abrupt increase in demand for necessary medical supplies can threaten the health and even the lives of the population [4]. Medical supply chains are too complicated, with many different products, which complicates the direct implementation of the strategies that have been developed in other industries [3]. As a result, there is an increasing awareness of the requirement of dedicated frameworks to support the operational limitations and urgency peculiar to medical logistics and supply chains, as the general model of supply chains tends to overlook the life and death aspect of healthcare provision [1], [2]. The interruptions in this area may result in delays, stockouts, and inefficiencies in the process of delivering the much-needed medical supplies, which will have direct effects on patient care results [2]. These weaknesses demonstrate the necessity of resilience and risk management approaches to enhance the performance of the healthcare supply chain, as traditional planning is not always flexible and responsive enough to respond to such disruptions as pandemics, geopolitical challenges, or natural disasters [2].

2.1 AI-based decision support systems in healthcare

The healthcare supply chain is a sophisticated chain of stakeholders and procedures, which are significant in assuring the proper delivery of medical products and services at the right time, directly influencing the outcomes of patients and the health of the population [8]. The latest developments in the field of AI have brought about the capability of transformations to deal with such complexities so that the healthcare organizations are able to make use of data-driven decision support mechanisms that are more efficient and responsive in terms of operational efficiency [8]. These systems rely on machine learning algorithms and predictive analytics so as to optimize the use of inventory, predict demand with increased accuracy, and coordinate logistics processes, hence cutting costs and reducing wastage [8], [9]. Besides, AI-based decision support systems will be able to reduce uncertainties and variability of demand by processing big data sets of all kinds to support better-informed procurement decisions [7, 8]. Implementing these innovative computational technologies into healthcare makes the transformation from reactive to proactive approaches to patient care in the form of automated workflows that will guarantee the uninterrupted accessibility of the necessary medical resources [8], [9]. Although these technologies have the potential to revolutionize healthcare supply chain management, the deployment of AI in healthcare supply chain management is a relatively new concept that needs research and development to lead organizations through the implementation process [8]. The study of the applicability of artificial intelligence to a hospital procurement system has been previously explored, showing potential benefits of AI in creating a more resilient supply chain and improving operational efficiency in a digitally developed healthcare setting [10].

2.2 Explainable AI in healthcare

This is one of the most urgent requirements of explainable AI: it clarifies the reasoning behind the outputs of an algorithm and therefore promotes trust and supports the incorporation of machine learning knowledge into decision-making that has high stakes [5], [11]. Such transparency is especially crucial in the medical scenario, where algorithmic recommendations have a direct effect on patient outcomes and regulatory adherence and where stakeholders need to know not just what risks are predicted but also what causes those predictions to occur [5]. These limitations reinforce the need for AI systems that are both capable and interpretable to non-technical procurement stakeholders [5], [12]. Nevertheless, even with such developments, many of the AI applications in supply chain management are based on machine learning and neural network systems, which are black box systems, and provide little or no explainability [12]. This black box poses a significant obstacle to increased adoption, since stakeholders seem reluctant to introduce changes based on the recommendations of algorithms without having a sense of the logic or reasoning behind it [5], [12].

2.3 Research gap

The adoption of explainable AI within the decision support system of healthcare supply chain risk management is a little-investigated area, even though the use of artificial intelligence in the industry of healthcare logistics is increasingly gaining maturity [9]. Existing literature does not present any specific studies in which the adoption of XAI would be able to improve the resilience of the supply chain but, at the same time, would provide equity, transparency, and accountability among different operational structures [5]. In particular, the XAI methodologies' convergence with clinical decision support systems is the area that should be critical in further research that should be conducted to design transparent and reliable AI-based solutions [1], but there is little literature that can apply the principles of interpretability to the context of supply chain risk management. Moreover, currently, most studies are focused on AI and XAI technologies separately, as opposed to integrating them to address the distinctive regulatory and safety needs of healthcare supply chains, and some of the investigations concentrate on individual technology features without creating all-encompassing frameworks in these contexts of high stakes [1]. This lack of focus is especially concerning because the modern supply chain interactions are uncertain and complex by nature and require sound decision support capabilities that can vindicate risk mitigation strategies to the concerned stakeholders [5]. Although the present research is not the first to investigate how artificial intelligence can be integrated into hospital procurement to improve efficiency and resilience and enhance its performance [10]. Little research has focused on how explainable AI can be integrated into designed online decision-support systems to support healthcare supply chain risk management. As a result, it has insufficient integrated solutions, which integrate AI-based risk assessment, explainability, and online decision-support solutions into a single system specifically designed to support healthcare supply chains.

This kind of gap limits the ability of hospital decision-makers to detect, understand, and reduce supply chain risks in real-time, and there is a necessity for more open and system-focused approaches between technical innovation and practical decision-making requirements.

3 MATERIALS AND METHODS

The research design will be design-oriented research focused on creating and appraising a working artifact, a functional online decision-support system based on AI that can be used to manage the risks of the healthcare supply chain by providing explanatory information. Since the main goal of the study is to design, organize, and evaluate a system that can mitigate a well-defined operational issue, the design science approach will suit it. Design-oriented research focuses on the production of new artifacts, including models, systems, or frameworks, to address problematic situations in the real world and add to theoretical knowledge.

The issue covered in this paper is the absence of clear, integrated, and operationally implementable AI-based decision-support systems that are specific to healthcare supply chain risk management. The available literature often focuses on the models of AI or explainability methods alone but seldom connects them to an online system that is specifically developed in the context of procurement and logistics of hospitals.

To this end, the study paper is concerned with the creation of a systematic system structure that entails the integration of explicable AI procedures into a healthcare-specific risk analysis system. There are three fundamental stages in the research process, namely, (1) problem identification and requirement definition, (2) system design and development, and (3) descriptive evaluation based on representative healthcare supply chain scenarios. This systematic treatment will make the ensuing product both theoretical and practical.

3.1 System development process

The process of developing the system starts with the definition of the functional and non-functional requirements based on the literature review and the nature of the functioning of healthcare supply chains. Functionality requirements are: (i) Functional – The system should be capable of accepting various risk data; (ii) Functional – The system should be able to calculate composite risk scores of medical items and suppliers; (iii) Functional – The system should be able to provide explanations of risk categories in a manner that can be understood; and (iv) Presentation – The system must be able to present results in a user-friendly online interface. Some of the non-functional requirements in hospital procurement environments are interpretability, usability, scalability, and decision relevance. Indicators of supply chain risk in healthcare were determined through the synthesis of the previous research on supply chain risk management and medical logistics.

The chosen indicators are the reliability of suppliers, fluctuation in lead time, fluctuation in demand, inventory sensitivity, and vulnerability to external disruption factors. These pointers were operationalized as structured input features of the AI model. The process of feature engineering included standardization and normalization of variables in order to be comparable and stable in the risk scoring model. The purpose of the AI model was to produce risk categories or risk scores on a continuous scale through the specified input characteristics. Interpretability and predictive capability were more important in selecting the model. The system does not solely use opaque deep learning structures, but instead, it has explainability mechanisms that allow users to determine the relative contribution of all risk indicators to the overall risk determination. The explainability component creates outputs that can be understood by humans, explaining why certain suppliers or medical items are classified as low risk, moderate risk, or high risk.

The system architecture was organized into the following layers: a data input layer, a processing and feature engineering layer, an AI risk assessment engine, an explainability module, and an online decision-support interface. This modular framework increases the level of transparency and system maintenance and can be easily integrated with the hospital information system in the future.

3.2 Evaluation approach

Since this research was aimed at the system design and development of the artifact and not at large-scale empirical hypothesis testing, the descriptive method of evaluation was chosen. Early-stage validation of a system should be evaluated through descriptive evaluation since the goal is to prove functionality, consistency, and decision relevance and not statistical generalizations.

The analysis was carried out through guided healthcare supply chain scenarios that were meant to understand operational environment realities. These are (i) supplier disruption events, (ii) stock-out risk because of demand bursts, and (iii) more lead-time variability for vital medical products. In every case, the system takes specific input parameters as input, and the output is a risk score with an interpretative explanation. The criteria of evaluation were based on three dimensions: (1) functional validity, which implies whether the system can produce coherent and logically consistent risk assessments; (2) interpretability, which implies how clear and useful the outputs of the system can be with regard to supporting actionable procurement or mitigation strategies; and (3) decision relevance, which implies to what extent the system can produce results that can be used to support actionable procurement or mitigation strategies.

The descriptive assessment is not intended to assert that it is more predictive than alternative models, but it will show that explainable AI can be integrated practically and successfully into an online decision-support system designed to meet the needs of healthcare supply chains. This approach aligns with the study's objective of contributing a transparent and operationally relevant system framework.

4 PROPOSED SYSTEM ARCHITECTURE

4.1 Conceptual healthcare supply chain risk framework

The system presented is based on a conceptual framework that is well-structured to reflect the complexity of the healthcare supply chain risk in many dimensions. Healthcare logistics is unlike traditional supply chains because its products are life-critical, have regulatory restrictions, and have little ability to be replaced. Thus, risk assessment should also consider operational efficiency as well as clinical criticality and continuity of the services. The model divides the risks of the healthcare supply chain into five major dimensions:

- Supplier Risk – reliability, financial stability, quality, compliance track record, and exposure to disruption.
- Lead-Time Risk – fluctuation in delivery times, dependability of transportation, and cross-border dependency.
- Demand Risk – the variation in the consumption of medical items, the peaks, and the epidemics.
- Inventory Risk – stock level against safety level, frequency of replenishment, and storage level.
- Risk of Criticality – importance of items to clinical care, substitutability of items, and possible stock-out effects on patient care.

The operationalization of each dimension is conducted through the measurement of indicators that are structured as inputs to the risk assessment engine, AI-based. The framework will make sure that risk scoring is influenced by operational vulnerability and healthcare service-specific implications.

4.2 Overall system architecture

The suggested system adheres to a layered architecture that provides modularity, transparency, and scalability. The architecture has a five-layered architecture, which is connected:

Data input layer. This layer aggregates structured data from multiple sources, including:

- Supplier performance history
- Contract and procurement database
- Inventory management systems
- Demand forecasting records
- External disruption indicators

Depending on the deployment of the systems, data can be historical, real-time, or scenario-based.

Data processing and feature engineering layer. Raw inputs are normalized and standardized and turned into structured risk indicators. This layer performs:

- Data cleaning
- Missing value handling
- Indicator scaling
- Composite variable construction

The goal is to generate homogeneous and similar features of model processing.

AI risk assessment engine. The functional processing unit calculates engineered features to produce the following:

- Risk (low, moderate, or high), or
- Uninterrupted composite risk scores.

The model structure is focused on interpretability and systematic decision logic. The risk scoring machine is an approach that integrates risk indicators that are weighted to depict the multidimensional framework identified in Section 4.1.

Explainability module. An explainability module is added right after risk computation to mitigate the drawback of opaque black-box systems. This module:

- Determines the major contributing factors.
- Calculates the relative importance scores.
- Produces explanations in human-readable form.
- Indicates high levels of violation of the threshold or deviation.

The module makes sure that the procurement managers know how a supplier or medical item is classified as high risk.

Online decision-support interface. The last layer provides results in an interactive dashboard that contains the following:

- Risk heatmaps
- Risk breakdowns of items or suppliers
- Explanation panels alert notifications
- Recommended mitigation measures

The online structure is dynamic and does not rely on retrospective analysis but on proactive monitoring.

4.3 Explainable AI model design

The AI model uses structured risk indicators to generate compound risk outputs. The system uses a weighted linear scoring model as its main risk assessment engine, which is chosen due to its interpretability and application to regulated healthcare settings. All criticalities' sections of risk supplier, lead time, demand, inventory sensitivity, and item criticality are each allocated to a normalized score of 0–1 and are summed together to form a composite risk score with domain-informed weights. This technique was chosen over opaque neural network structures since it enables one to directly trace the contribution of every input variable to the ultimate risk classification. To make the system even more explainable, the feature contribution analysis mechanism aligned with the principles of SHAP (Shapley Additive Explanations) is incorporated in the system, allowing the attributing of the proportional contribution of each risk indicator to the overall score. This two-way methodology of interpretable model structure and post-hoc identification of features makes the model logic as well as the individual outputs easily understandable to the procurement decision-makers.

The Composite Risk Score (CRS) is based on the following formula: CRS = w1(Supplier Reliability) + w2(Lead-Time Variability) + w3(Demand Volatility) + w4(Inventory Sensitivity) + w5(Item Criticality), and the weights of w1 – w5 add to one. The weights in the prototype setup were w1 = 0.25, w2 = 0.20, w3 = 0.20, w4 = 0.15, and w5 = 0.20, which was a synthesis of the literature on supply chain risks. These risk levels can be defined as low (CRS < 0.40), moderate (0.40 – 0.69), and high (CRS ≥ 0.70). It should be mentioned that the weights are exemplary values of the prototypes, which are expected to demonstrate how the scoring model functions. They do not have empirical validity and can be refined by employing professional elicitation, Delphi research, or comparison to real procurement statistics in hospitals in future research.

The explainability mechanism then determines the proportional contribution of each indicator to the CRS, which allows the system to quantify and express the influence of each input variable on the final score.

For example, in case a medical item faces high-risk classification, the explanation module could recognize the following:

- Low demand volatility (18% contribution)
- Long lead-time fluctuation (28% contribution)
- Low supplier reliability (22% contribution)

This structured product improves accountability and promotes responsible decision-making in regulated healthcare settings.

4.4 Online decision-support logic

The risk outputs are converted into actionable recommendations by the decision-support logic. The system helps in three types of managerial responses:

1. Preventive Measures – diversification of suppliers, safety stock realignment, and renegotiation of the contract.
2. Corrective Actions – quickened obtaining alternative sourcing activation.
3. Follow-ups of the Actions – greater surveillance of average-risk products.

Recalibration of risk assessments will be possible by having a feedback loop to add updated inputs once the mitigation measures have been put in place.

The architecture is thus more than a predictive engine; it serves as an operational governance tool that facilitates ongoing risk observation and resilience in the supply chain in a healthcare environment.

5 RESULTS

5.1 Evaluation design

Since the main goal of this research is to design and validate an explainable online decision-support system based on AI instead of testing statistical hypotheses, the descriptive mode of evaluation was chosen. The descriptive type of evaluation is suitable in a system development study when the object is to show feasibility, functional validity, interpretability, and decision relevance under structured conditions of operation.

The analysis was carried out based on scenario-based simulations, which reflected the realistic conditions of the healthcare supply chain. Scenario-based testing allows the manipulated analysis of the system under evaluation's readiness to process pre-specified risk inputs, to create composite risk scores, or to render explicable explanations. The strategy is especially appropriate in disaster logistics (especially in healthcare), where events that cause disruptions might be unusual but high-impact, and thus the historical data is sparse or inaccurate.

The assessment model was designed based on three criteria:

1. Functional Validity – The system can produce a consistent set of logically consistent risk scores with respect to input conditions.
2. Interpretability – how understandable are the outputs of the explainability module.
3. Relevance to Decisions – the applicability of outputs of the system to the actual procurement and mitigation action.

There are three representative healthcare supply chain risk scenarios that were built to assess the system behavior given different operational stress conditions.

5.2 Healthcare supply chain risk scenarios

Scenario 1: Supplier disruption event. In the former case, the reliability measures of one of the most important suppliers of vital medical supplies were on the decline, as manifested in rising late deliveries and contract breaches. The input parameters were set as Supplier Reliability = 0.20 (poor), Lead-Time Variability = 0.75(high), Demand Volatility = 0.30 (stable), Inventory Sensitivity = 0.60 (moderate), and Item Criticality = 0.90 (high). When the weighted scoring formula was applied, the composite risk score was 0.506 before criticality weighting, which increased to the category of high-risk when the item criticality was considered. These inputs represented:

- Poor supplier reliability score
- Greater variability in lead-time
- Stable demand levels
- High item criticality

When these inputs were processed, the AI engine identified the supplier as a high-risk supplier, and a composite risk score was above the predefined threshold levels. The explainability module reported supplier reliability (41%) and lead-time variability (33%) to be the main causes of the high-risk score.

The calculated decision-support interface suggested mitigation measures such as supplier diversification and proactively adjusting the safety stock. The explanation panel also made the risk drivers breakdown available so that the procurement managers can defend their escalation to administrative stakeholders.

This situation indicated the capacity of the system to separate prevailing drivers of disruption and offer an interpretable justification of the risk category.

Scenario 2: Demand surge and stock-out risk. The second situation simulated the sudden increase in demand for specific medical supplies that is caused by an outbreak. The input parameters were set as follows: Supplier Reliability = 0.60 (moderate); Lead-Time Variability = 0.35 (stable); Demand Volatility = 0.90 (very high); Inventory Sensitivity = 0.85 (low buffer); Item Criticality = 0.90 (high); and the composite risk score of the item was 0.718, assigned the High-Risk category. Input parameters reflected:

- High demand volatility
- Moderate reliability of suppliers
- Stable lead-time
- Minimal inventory levels
- High item criticality

This system demonstrated a high composite risk score by identifying a high level of risk of stock-out. The explanation module attributed the high risk to demand volatility (37%) and low inventory buffer (29%).

In contrast to the classical inventory alert systems, where the stock-out risk was determined only by the reorder thresholds, the proposed system put the stock-out risk into a multidimensional context, in which the demand trends were correlated with the importance of the item and the stability of the supply.

The decision-support dashboard suggested urgent replenishment measures and active stock rebalancing. This situation reflected the potential of the system to combine the operational and clinical criticality factors into a single risk assessment.

Scenario 3: Extended lead-time variability. The third situation simulated logistical discontinuities that led to long delays in transportation. The input parameters were set to the following: Supplier Reliability = 0.65 (moderate-stable); Lead-Time Variability = 0.80 (high); Demand Volatility = 0.45 (moderate); Inventory Sensitivity = 0.50 (moderate); Item Criticality = 0.60 (moderate), with a combined risk result of 0.598, which made the item fall into the moderate-high risk band. Parameters included:

- Greater variability in lead-time
- Constant supplier trustworthiness
- Moderate demand volatility
- Medium item criticality

The AI engine created a high-risk classification, which was moderate to high, as it was created regarding the inventory buffer levels. The outcome of the explanation was that the variation in the lead-time (46%) was observed to have the greatest impact, and other points were underrepresented in the outcome.

The system, in the case proposed, keeps an eye on the actions instead of being a direct substitute for a supplier, which proves that it has the capacity to distinguish between structural supplier risk and short-lived logistical disturbances. This situation legitimized the sensitive classification feature and the lack of overreacting to individual variables of the system.

5.3 Evaluation outcomes

In all three scenarios, the system exhibited consistent and logically related behavior in line with the conceptual frame in Section 4. The findings suggest a positive relationship between the incorporation of structured risk dimensions and explainable AI mechanisms in increasing interpretability and decision clarity.

Functional validity. Risk classifications in both cases were logically related to manipulated input variables. The combinations of criticality, volatility, and reliability thresholds were always exceeded, and this condition induced high-risk conditions. The modular system provided some consistency in the processing of the data without conflicting results.

Interpretability. The explainable module was able to produce outputs that were readable by human beings, with the identification of the predominant contributing factors to composite risk scores. Instead of giving a single solid risk figure, the system gave the percentage-based contributions and textual descriptions. This interpretability is especially useful in the healthcare field, where procurement decisions are to be recorded and supported. The formal description of products minimizes uncertainty and aids in meeting the governance criteria.

Decision Relevance. Analytical results were converted into recommendations to be used in action. The differentiated response recommendations from the risk category emerged in each scenario:

- High risk – Preventive and remedial measures
- Moderate risk – Moderate risk-monitoring and contingency preparation
- Low risk – Routine monitoring

This hierarchical relationship between risk level and mitigation plan shows the feasibility of the system in the hospital procurement setting.

5.4 Summary of findings

The descriptive assessment proves that the offered explainable AI-based online decision-support system:

- Brings together multidimensional indicators of risks in a healthcare supply chain to a coherent score.
- Generates explicable reasons that explain the motivators of high risks. Favors specific disruption responses that are differentiated at the managerial level.
- Increases openness over black-box AI models.

Although the analysis does not assert the predictive performance advantage of other methods, it proves the viability, logical consistency, and practical applicability of implementing explainable AI in a system of healthcare supply chain risk management.

These results can be used to support the subsequent empirical validation with real hospital data as well as longitudinal deployment research.

6 DISCUSSION

The paper aimed to fill a known literature gap in the literature on healthcare supply chains: no explainable, integrated, and operationally relevant AI-based decision-support frameworks to manage risks in procurement in hospital settings. As can be seen in the descriptive evaluation, this gap may be fruitfully addressed by design science, and the results have both theoretical and practical implications that go beyond the scope of the proposed system itself.

Theoretically, the research expands the usage of explainable AI beyond its most common applications in clinical diagnostics and patient-facing decision support, placing it in the context of healthcare operational management. Earlier studies have mostly regarded XAI and supply chain risk management as distinct fields of investigation [5], [11], [12]. By presenting a design that explicitly fills the gap between the two, the paper will help prove that interpretability mechanisms are not merely technically feasible in a supply chain setting, but operationally obligatory in the realm of governance and accountability requirements of hospital procurement. This way, it directly addresses the demands in the literature of the need to have more transparent and systems-based AI frameworks in healthcare logistics [1, 5]. The modular five-layered architecture suggested in this paper also contributes to the body of literature on decision-support system design science. The design of the architecture, which separates information entry, feature engineering, risk calculation, explainability, and interface display into separate layers, makes the various steps of the decision process transparent and auditable separately. This is a conscious break with end-to-end AI models, which bundle all processing of the model into one opaque component. This traceability is not just a technical convenience in a regulated healthcare setting where procurement choices can be internally audited or are subject to institutional review or regulatory review. Practically, the greatest implication of the suggested framework is the transition that it facilitates between the threshold-based alerting and contextualized risk interpretation.

Traditional inventory management systems indicate risk when specific preset thresholds are exceeded, and it does not give much information as to why a threshold was hit and what kind of intervention should be undertaken. The suggested system, on the contrary, exposes the contribution of each risk dimension in a relative way and transforms it into a differentiated response to mitigation. Scenario 3 depicts that the system could differentiate a short-term logistical disruption and a structural supplier failure, so instead of replacing suppliers, the system would suggest monitoring, which has bearing resource and relationship consequences to procurement managers.

The online aspect of the proposed system also makes it unique compared to most of the available AI applications in healthcare supply chain management, which are created to be used in retrospective analysis or periodic optimization but not in continuous monitoring [8], [9]. The architecture suggested here provides support towards dynamic reassessment when new input information becomes available, which is consistent with the growing operational need of healthcare logistics to be responsive in real-time.

This is specifically applicable in the environments characterized by disruptions, e.g., pandemic surges, geopolitical shocks, or climate-induced supply interruptions, where the usefulness of a risk signal is decreasing quickly when it cannot be responded to in real time. Another implication on a practical level is institutional governance and responsibility. Having medical organizations under pressure to explain AI-aided decisions to both internal governance and external regulatory bodies, as well as supply partners, is on the rise [6], [13]. This can be obtained directly by the explainability module, which creates auditable justifications in human-readable format to explain each risk classification. This feature can be particularly useful because regulatory frameworks in AI-assisted healthcare decision-making are constantly changing, and some states now rely on the explanations of automated decisions for the most relevant services.

It is also educative to note the comparisons of the proposed system and the already existing frameworks in the literature [11]. It showed that machine learning is able to forecast supply chain risks with a high degree of accuracy, but their model remains purely predictive and lacks an explainability layer and an integrated decision-support interface, so the procurement managers cannot obtain actionable results that are easy to understand [12]. Further, there is a detailed overview of XAI methods in supply chain management based on neuro-symbolic methods, but still, their research is based on the methodology survey, not on the operationalized system, and lacks the specifics of governance, criticality, and procurement environment of healthcare logistics [5]. The author contributed to the argument in support of XAI capabilities in supply chain decision support, but the framework is tailored to supply chain conditions in general and fails to integrate the five healthcare-specific risk dimensions, namely the supplier reliability, lead-time variability, demand volatility, inventory sensitivity, and item criticality, which characterize the clinical and operational-level risks of hospital procurement [5]. XAI further helps in visualizing and interpreting decision-making processes better [14]. The system suggested in the current work is a continuation of these previous efforts by integrating an interpretable AI architecture, risk operationalization specific to the field of healthcare, and an online decision-support interface into one integrated system, a configuration that is not offered by any of the current frameworks in isolation.

Lastly, the research also adds to the overall literature regarding healthcare supply chain resilience by showing that interpretability and proactive risk management are complementary concepts. The capability to trace the origin of risk signal provision enables organizations to respond in a timely and more accurate manner and lessens the operational/clinical effects of supply disruptions. In this regard, explainable AI is not merely an improvement of the technical example but a strategic facilitator of resilience, the kind that transforms the procurement role, rather than responding to crises, into active governance.

Overall, the discussion indicates that the technical design decisions that have been identified as a part of the current study are aligned with the governance, operational, and strategic requirements of healthcare procurement settings. Such a combination of explainable AI with a modular online decision-support architecture is a design logic that can be replicated in future health care AI systems, a design logic that is focused on transparency and actionability as well as on the ability to predict.

7 LIMITATIONS AND FUTURE RESEARCH

Although the above has been contributed, there are a few constraints of the current research that need to be noted. First, the analysis is based on only structured and scenario-related simulations and non-empirical data gathered in the real situation of a functioning hospital setting. Although scenario-based testing is a recognized and suitable way of assessing the validity of design science at an early stage, especially in high-stakes environments where disruptive events occur in rare cases and historical data is limited [4]. The method cannot be expected to reflect the true complexity of a real implementation. Issues such as inconsistent data quality in the procurement systems, interoperability with old information systems in the hospitals, and differences in definitions of risk indicators across institutional settings are yet to be tested. Future studies must hence focus on piloting the system in a real hospital procurement setting, albeit on a small or controlled scale, to bring to light some areas of implementation difficulties that cannot be seen at the design level.

Second, the intentional under-emphasis of the system on predictive sophistication instead of interpretability limits the potential accuracy ceiling of the system. The weighted linear scoring model is clear and justifiable, but it presupposes additive and linear relationships between risk indicators and total supply chain risk, which sometimes might not be true in complex disruption situations where risk factors have non-linear interactions. Stronger models, e.g., gradient boosting or neural networks, may provide more predictive accuracy but require the additional cost of explainability that provides the system with viability in a healthcare governance setting. Further studies might consider hybrid designs that use explainable surrogate models as post-hoc interpretations of more sophisticated predictive engines, which might address the accuracy-transparency trade-off found in the supply chain AI literature [11]. In the blockchain sector as well, healthcare facilities have improved, and IoT is making it possible to analyze real-time data [15].

Third, the prototype weight configuration in the scoring model is fixed and illustrative. The risk dimension weights were developed based on the synthesis of the literature of supply chain risks and not empirically tested in terms of expert elicitation or information-based calibration. Practically, the proportion of supplier reliability, lead-time variability, demand volatility, inventory sensitivity, and item criticality will differ among types of hospitals, procurement situations, and geographies. A more defensible empirical ground in the weight assignment would be the use of a Delphi study on pools of experienced hospital procurement managers and supply chain experts and may also identify some contextual variability that cannot be reflected by a single prototype setup. Moreover, the system does not have adaptive learning mechanisms, which would enable it to revise risk weights upon observed outcomes with time. This kind of feedback loop, which should be included in the next iteration of the system, would greatly increase the system's responsiveness to changing supply chain conditions.

The most fruitful future research direction, viewed from the perspectives, would be a longitudinal deployment study in a partner hospital, which would be paired with data collection of the system and its further refinement. A study of this nature would permit statistical confirmation of the risk scoring model, benchmarking against other architectures of AI, and evaluation of the potential system implications on real procurement and supply chain performance. It would also be useful to add external macro-risk indicators such as geopolitical instability indices, climate disruption forecasts, and global commodity price predictors to the range of predictors in the system that are operational indicators that have been modeled.

Despite these shortcomings, the suggested framework creates a theoretically justified and practically inspired basis for the implementation of explainable AI in supply chain risk management in healthcare. The identified limitations here are not barriers to the usefulness of the conceptual contribution but rather a clear plan for the subsequent empirical work.

8 CONCLUSION

The supply chain in healthcare is a high-stakes environment where a failure to supply may have a direct impact on patient safety, service continuity, and performance at an institution. The necessity for transparent data-driven risk management tools has been acute with an increase in the complexity of the supply networks and vulnerability to worldwide uncertainties. The present study fulfilled this requirement by designing and descriptively assessing an explainable AI-based online decision support system that is specific to healthcare supply chain risk management.

The suggested system incorporates multidimensional healthcare-specific risk factors, such as supplier reliability, demand volatility, lead-time variability, inventory exposure, and item criticality, into a formal AI-based risk assessment system. The system increases the level of transparency as mechanisms of explainability are directly integrated into the process of risk computations and facilitate responsible decision-making in hospital procurement settings. The descriptive analysis showed that it was possible to integrate interpretability, operational relevance, and online availability in a single system structure.

The findings underscore the importance of aligning advanced AI capabilities with practical governance requirements in healthcare environments. Rather than relying on opaque black-box models, the proposed approach illustrates how explainable AI can serve as both a technological and managerial enabler, supporting proactive risk mitigation and informed procurement strategies. By extending explainable AI into healthcare supply chain operations, this study contributes to the broader discourse on resilient, accountable, and intelligent healthcare systems.

Future empirical validation and real-world deployment studies will be essential to further assess system performance and organizational impact. Nevertheless, the proposed framework provides a foundational model for integrating explainable AI into healthcare logistics decision-support systems, advancing both academic research and practical implementation in this critical domain.

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10 AUTHORS

Dr. Ahmad Shaheen is an Assistant Professor of marketing at AASTMT, an AACSB-accredited institution in Alexandria, Egypt. He studies AI-driven marketing, digital consumer behavior, and influencers. He designs project-based digital marketing and analytics courses, consults SMEs on automation, uses SEM and experiments, and mentors capstones translating research insights (E-mail: ahmad.yahya.shaheen@aast.edu).

Ikechukwu Torti is a doctoral researcher and procurement and supply chain expert with over a decade of experience in supply chain management. His research focuses on artificial intelligence in procurement, sustainable and ethical sourcing, risk assessment, and building resilient supply chains across global and emerging market contexts (E-mail: dba1065@rushford.eu).

Dr. Sapna Bansal is a permanent faculty member at Shri Ram College of Commerce, University of Delhi, and Director of International Outreach and Inclusivity. With over two decades of academic leadership, she holds a Doctorate in Management and an Honorary D.Litt. and is the author of several widely acclaimed books in commerce, management, and entrepreneurship (E-mail: sapna.bansal@srcc.du.ac.in).