



# Information Fusion from Multimodal Clinical Sensors for Effective Supplier Decision-Making in Healthcare

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## Abstract

Effective procurement of clinical devices in healthcare demands a sophisticated decision-making approach integrating diverse data sources from multiple devices, brands, and suppliers, particularly within the context of information fusion. This study addresses this challenge by proposing an improved best-worst method harmonized with information fusion techniques and multi-criteria decision-making methodologies. The background emphasizes the dynamic nature of healthcare procurement, necessitating systematic strategies for navigating the complexities of device selection and integration. Recognizing the intricacies inherent in this challenge, the problem statement revolves around enhancing the best-worst method to amalgamate data from clinical devices while concurrently evaluating brands and suppliers. This aims to optimize performance and minimize costs within the information fusion paradigm. Our proposed methodology introduces an augmented best-worst approach, encompassing weighted criteria assessment for clinical devices, brands, and suppliers, providing a more adaptable and nuanced decision-making framework tailored to the information fusion landscape. The results showcase a structured evaluation matrix derived from refined weighted criteria, elucidating the relative performance and strengths across various entities within the healthcare procurement ecosystem. Emphasizing reliability, compatibility, innovation, and quality assurance, this process highlights pivotal factors influencing procurement decisions within the realm of information fusion.

**Keywords:** Healthcare Supply Chain; Decision Support Systems; Information Fusion; Supplier Selection; Multimodal Data Integration; Procurement Strategies; Decision-making Processes.

## 1. Introduction

In contemporary healthcare systems, the convergence of technological advancements and data-driven methodologies has revolutionized the landscape of decision-making processes, particularly in the context of supplier selection [1-2]. The burgeoning utilization of clinical sensors across healthcare facilities has generated a wealth of diverse, multi-dimensional data streams. Information fusion, as a strategic approach, has emerged as a pivotal mechanism for integrating and synthesizing heterogeneous data derived from these multimodal clinical sensors. This fusion process involves amalgamating data from various sources and modalities to derive comprehensive, enriched insights that transcend the individual capabilities of each sensor. It presents a promising avenue for enhancing the accuracy, reliability, and depth of information available for critical decision-making within healthcare supply chain management [3-5].

Simultaneously, the realm of Multi-Criteria Decision-Making (MCDM) frameworks has gained substantial traction in enabling systematic and structured decision processes. MCDM techniques provide a robust methodology for evaluating and ranking supplier alternatives by considering multiple conflicting criteria or objectives [6-8]. These

methodologies offer a quantitative and qualitative framework to manage complex decision scenarios, aligning with the intricate nature of supplier selection in healthcare, where diverse criteria encompassing cost, quality, reliability, and service level agreements often intersect [9].

However, within the context of healthcare supply chain management, despite the advancements in information fusion and MCDM techniques, challenges persist in leveraging the full potential of integrated clinical sensor data for effective supplier decision-making. The amalgamation of diverse data sources from clinical sensors into a cohesive, actionable format remains a significant obstacle [10-13]. This paper aims to address this gap by proposing a comprehensive framework that exploits the potential of information fusion from multimodal clinical sensors to optimize the supplier decision-making process in healthcare. The primary objective of this work is to develop a systematic approach that harnesses information fusion techniques alongside MCDM methodologies to enhance the accuracy and efficacy of supplier selection, thereby contributing to improved operational efficiency and patient care within healthcare organizations.

The paper is structured into five main sections: Section 2 delves into an exploration of Related Works, offering a comprehensive review of existing literature and research pertinent to the fusion of information from multimodal clinical sensors and its application in supplier decision-making within healthcare. Section 3 elucidates the Methodology employed in this study, delineating the proposed framework that integrates information fusion techniques with MCDM methodologies to optimize the selection process for healthcare suppliers. Section 4 elucidates the Experimental Design, detailing the specific procedures and methodologies utilized in gathering and processing data, as well as the setup of experiments conducted to validate the proposed framework. Section 5 presents the Results and Discussion, offering a comprehensive analysis and interpretation of findings derived from the experiments, along with a detailed discussion on the implications and significance of the results in the context of supplier decision-making within healthcare. Lastly, Section 6 encapsulates the Conclusion, summarizing key insights, outlining contributions, and providing avenues for future research based on the study's outcomes.

## **2. Related Works**

In this section, an extensive examination of the Related Work is presented, aiming to provide a comprehensive overview and critical analysis of the existing body of literature concerning the fusion of information derived from multimodal clinical sensors for the purpose of enhancing supplier decision-making within the healthcare domain. Chakraborty et al. [14] offered a systematic review of MCDM methods in healthcare. Their work extensively outlined various methodologies and applications of MCDM, emphasizing their significance in enhancing decision-making processes within the healthcare domain. They likely analyzed and synthesized multiple studies, providing an overarching perspective on the effectiveness and applicability of diverse decision-making frameworks.

Li et al. [15] focused on multi-attribute group decision-making considering opinion dynamics, a significant aspect in decision processes. Their research might have incorporated methodologies that accounted for the dynamic nature of opinions within a group, perhaps utilizing models that capture the evolution of opinions over time and their influence on decision outcomes. Cobuloğlu and Büyüktaktın [16] proposed a stochastic Multi-Criteria Decision Analysis (MCDA) for sustainable crop selection. This study likely involved probabilistic models or methods to account for uncertainties in decision-making related to sustainable crop selection, emphasizing the importance of considering uncertainty in sustainable solutions. Sun et al. [17] introduced a decision-making method utilizing grey multi-source heterogeneous data for green supplier selection. This likely involved techniques for handling heterogeneous data sources and integrating them into decision-making frameworks specifically tailored for environmentally conscious supplier choices. Snášel et al. [18] generalized a multi-source fusion-based framework for stock selection, indicating adaptability across various domains. This work likely focused on creating a generalized model that amalgamates information from diverse sources for the purpose of stock selection, showcasing the flexibility and applicability of fusion-based models. Zhou et al. [19] evaluated simulation credibility through multi-source data fusion techniques, contributing to the assessment of simulation results. This study probably delved into methodologies that assessed the credibility of simulation outcomes through the fusion of data from multiple sources, emphasizing the importance of robustness and reliability in simulation studies. Tang, Chen, and Zhou [20] focused on measuring uncertainty in negation evidence, an essential aspect for refining multi-source information fusion processes. Their work likely delved into methodologies for quantifying uncertainty arising from negation evidence, providing insights into managing and refining fusion processes under uncertain scenarios.

Snášel et al. [21] introduced a fusion-based model with a customized loss function for stock selection. This likely involved tailoring fusion models with specific loss functions to optimize decision-making processes in stock selection, showcasing the significance of customized approaches in decision frameworks. Zhang and Chen [22] proposed a multi-criteria group decision-making method integrating cloud model and TOPSIS under uncertainty, offering insights into handling uncertain scenarios in decision-making. Their work likely incorporated cloud-based models and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) to address decision-making under uncertainty, emphasizing robustness in multi-criteria group decisions. Sodenkamp et al. [23] introduced an aggregation method for solving group multi-criteria decision-making problems with single-valued neutrosophic sets. This study likely explored methodologies that aggregated decision-making information involving single-valued neutrosophic sets within a group context, contributing to problem-solving strategies in decision-making scenarios.

Liu et al., [24] employed DEMATEL (Decision-Making Trial and Evaluation Laboratory) and game theory in evidential supplier selection, enriching decision-making processes. Their research might have involved using DEMATEL to model causal relationships and game theory for analyzing strategic interactions in supplier selection, enhancing the depth and robustness of decision-making frameworks. Wang and Xiao [25] devised an improved multi-source data fusion method based on belief entropy and divergence measure, refining fusion techniques. This study introduced advanced fusion techniques that incorporated belief entropy and divergence measures, aiming to enhance the accuracy and reliability of multi-source data fusion processes. Zhang et al. [26] introduced a multi-source information fusion method for ship target recognition, highlighting the application of fusion in target identification systems. Their work likely focused on developing fusion methodologies tailored for ship target recognition, emphasizing the significance of fusion techniques in enhancing recognition accuracy and reliability. El-Douh et al. [27] presented a neutrosophic multi-criteria model for evaluating sustainable soil enhancement methods in construction, emphasizing sustainability considerations in decision-making. Their research likely involved developing a model that accounted for multiple criteria using neutrosophic logic, emphasizing the significance of sustainability in evaluating soil enhancement methods. Huang et al. [28] proposed a multi-criteria group decision-making method for green supplier selection based on distributed interval variables, contributing to environmentally focused supplier choices. Their work likely introduced methodologies that accounted for distributed interval variables in decision-making for selecting green suppliers, aligning with environmentally conscious practices. Fei et al. [29] introduced an ELECTRE-based MCDM method using Dempster-Shafer theory for supplier selection, offering a nuanced approach to decision-making considering uncertain information sources. This study likely employed the ELECTRE (Elimination and Choice Translating Reality) method alongside Dempster-Shafer theory to handle uncertainty in supplier selection, providing a refined approach to decision-making in uncertain scenarios.

### 3. Methodology

This section elucidates the methodological framework developed to integrate information fusion techniques with MCDM methodologies, aiming to optimize the process of clinical supplier selection within the healthcare domain. This section delineates the systematic approach designed to address the complexities inherent in leveraging multimodal clinical sensor data for informed decision-making. The proposed methodology draws upon established principles from information fusion, MCDM, and related fields, offering a structured and comprehensive framework to amalgamate heterogeneous data streams from clinical sensors and derive actionable insights for supplier assessment.

the Best-Worst Method (BWM) is a multi-criteria decision-making technique used for subjective weighting of criteria. It involves several steps to determine the relative importance or weights of criteria based on the best and worst alternatives within a decision-making context. Below are the steps along with relevant mathematical terms and formulae used in the application of the BWM:

**Step 1: Determination of Decision Criteria** The initial phase involves identifying and defining a comprehensive set of decision criteria relevant to the context of supplier selection in healthcare. These criteria encompass various facets such as cost-effectiveness, quality assurance, delivery reliability, and service level agreements among others. Each criterion serves as a pivotal parameter influencing the supplier selection process.

**Step 2: Identification of Best and Worst Criteria** Following the establishment of decision criteria, the next step involves identifying the best and worst criteria within the defined set. The best criterion represents the most favorable and essential aspect, while the worst criterion signifies the least desirable attribute in the context of supplier selection.

Step 3: Preference Assessment for the Best Criterion A numerical preference is assigned to the best criterion concerning its importance or desirability compared to all other criteria in the set. This assessment involves utilizing a numerical scale ranging from 1 to 9, where a higher score signifies greater preference or significance of the best criterion relative to others.

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}), \tag{1}$$

Step 4: Preference Assessment for the Worst Criterion Similarly, a numerical preference is assigned to the worst criterion concerning its undesirability compared to all other criteria. Using the same numerical scale from 1 to 9, a lower score is designated to indicate the lesser preference or significance of the worst criterion relative to others.

$$A_B = (a_{1W}, a_{2W}, \dots, a_{nW})^T \tag{2}$$

Step 5: Calculation of Optimal Weights By applying the Best Worst Method, the optimal weights  $(w_1^*, w_2^*, \dots, w_n^*)$  for each criterion are computed based on the preferences derived from Steps 3 and 4. These weights represent the relative importance of each criterion in the supplier selection process, considering both the best-to-others and others-to-worst preferences. The optimal weights obtained through this method contribute to establishing a structured and informed framework for effectively evaluating and ranking supplier alternatives in healthcare procurement processes.

Considering the non-negativity and sum condition for the weights, the following problem is resulted:

$$\left\{ \begin{array}{l} \min[\max_{1 \leq j \leq n} (|a_{Bj}w_j - w_B|, |a_{jW}w_W - w_j|)] \\ \sum_{j=1}^n w_j = 1 \\ 0 < w_W \leq w_j \leq w_B \forall j \end{array} \right. \tag{3}$$

The hospital administration aims to procure a range of clinical gadgets that have the capability to connect with an Internet of Things (IoT) platform. The procurement process entails the selection of different types of therapeutic devices that meet specific requirements from a variety of vendors, referred to as retailers within the context of our study. These companies provide a variety of therapeutic gadgets from various brands. One of the primary difficulties lies in the assessment and quantification of the efficacy of various clinical device categories, manufacturers, and supplier collections. The decision-making scenario at hand is complex as it involves the evaluation of several factors in assessing clinical device kinds, brands, and vendor offerings. This strongly relates to the concept of information fusion.

The individual responsible for making decisions in this particular scenario seeks to achieve two main goals: maximizing the efficiency of the therapeutic gadgets that have been obtained, while simultaneously limiting the expenditures that are associated with them. This represents a unique example of a multi-objective optimization problem. Significantly, the incorporation of these medical devices with an Internet of Things (IoT) platform emerges as a crucial factor to be taken into account in the decision-making procedure.

To tackle the complex challenge of vendor selection, our proposed technique entails the creation of a hybridized multi-criteria approach. This approach combines a performance assessment model with a multi-objective optimization framework. The decision process employed in our hybrid model consists of four primary stages:

Stage 1. The process involves the establishment of a clear and concise definition of the decision problem at hand, as well as the collection of relevant input data that is specifically customized to the intricacies and requirements of information fusion. All input data in all stages are symbolized as depicted in Table 1.

Table 1: details of symbols in our methodology.

Input	Symbols	Criteria	
Types of clinical devices	$D_1, D_2, \dots, D_n$	$C = \{C_1, C_2, \dots, C_o\}$	$q_i^D$
Brands	$B_1, B_2, \dots, B_m$	$\bar{C} = \{\bar{C}_1, \bar{C}_2, \dots, \bar{C}_r\}$	$q_j^B$

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<b>Suppliers</b>	$V_1, V_2, \dots, V_p$	$\bar{C} = \{\bar{C}_1, \bar{C}_2, \dots, \bar{C}_s\}$	$q_k^V$
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Stage 2, The weights for criteria pertaining to clinical devices, brands, and suppliers can be determined using an improved best worst method, which enables a thorough and nuanced evaluation. The weights of inputs are computed as follows:

$$w_l = \frac{1}{a_{Bl} \left( \sum_{y=1}^o \frac{1}{a_{By}} \right)}, l = 1, 2, \dots, o \tag{4}$$

$$\bar{w}_u = \frac{1}{\bar{a}_{Bu} \left( \sum_{y=1}^r \frac{1}{\bar{a}_{By}} \right)}, u = 1, 2, \dots, r \tag{5}$$

$$\bar{\bar{w}}_v = \frac{1}{\bar{\bar{a}}_{Bv} \left( \sum_{y=1}^s \frac{1}{\bar{\bar{a}}_{By}} \right)}, v = 1, 2, \dots, s \tag{6}$$

Stage 3. The aim of this study is to do a comprehensive review of clinical devices, brands, and vendor offerings in order to gain significant insights into their effectiveness and applicability within the information fusion paradigm. The performance of each input is given as follows:

$$q_i^D = \sum_{l=1}^o w_l * t_{il}^N; q_j^B = \sum_{u=1}^r \bar{w}_u * \bar{t}_{ju}^N; q_k^V = \sum_{v=1}^s \bar{\bar{w}}_v * \bar{\bar{t}}_{kv}^N \tag{7}$$

Stage 4. Utilizing a multi-objective optimization methodology to address and ascertain the most suitable clinical device types, brands, and vendors, while aligning these selections with the overarching objectives of maximizing performance and lowering costs within the framework of information fusion-enabled healthcare systems.

#### 4. Results and Discussion

This section constitutes the culmination of empirical findings and critical analyses obtained from the implementation of the proposed framework integrating information fusion techniques with MCDM methodologies for clinical supplier selection within the healthcare domain. This section presents a comprehensive synthesis of the results obtained from the conducted experiments, delineating key observations, performance metrics, and insights derived from the application of the fusion-based decision-making model.

In our comprehensive case study, we delved into the fusion of data obtained from seven distinct clinical devices: the Electrocardiogram (ECG), Spirometer, Infusion Pump, Ultrasound Machine, Patient Monitor, Portable X-Ray Machine, and Defibrillator. These devices collectively offer a wide array of diagnostic, monitoring, and therapeutic functionalities within healthcare settings. The amalgamation of data sourced from these diverse clinical devices provides a multi-dimensional view of patients' health status, ranging from cardiac rhythm assessment (ECG) and respiratory function analysis (Spirometer) to intravenous medication delivery (Infusion Pump), imaging diagnostics (Ultrasound and X-Ray), real-time vital sign monitoring (Patient Monitor), and emergency cardiac care (Defibrillator). Within this case study, we explore the fusion of data generated by these devices to derive comprehensive patient insights, thus facilitating informed and holistic healthcare decision-making. The evaluation

and selection process of clinical devices and their respective suppliers involve a systematic assessment based on various criteria. Table 2 delineates the crucial brand criteria used to evaluate and rank clinical device brands within healthcare procurement. These criteria encompass aspects such as reliability, compatibility, durability, innovation, and service support, crucial for ensuring optimal performance and seamless integration of devices into healthcare systems. Similarly, Table 3 outlines the diverse supplier criteria essential for assessing and choosing appropriate suppliers. These criteria encompass quality assurance, cost-effectiveness, delivery timeliness, warranty, technological expertise, customer feedback, scalability, ethical standards, customization flexibility, and sustainability practices. The meticulous examination of these criteria forms the bedrock of our decision-making process, facilitating the selection of both clinical devices and suppliers that align closely with the demands of our healthcare setting, ensuring efficiency, reliability, and ethical compliance in device procurement and utilization.

Table 2: Criteria for Evaluating Clinical Device Brands in Healthcare Procurement

<b>Criteria</b>	<b>Description</b>
<b>Reliability</b>	Consistency in device performance and accuracy of readings.
<b>Compatibility</b>	Ability to seamlessly integrate with existing systems and technologies.
<b>Durability</b>	Longevity and robustness of devices under various operating conditions.
<b>Innovation</b>	Incorporation of advanced features or technological advancements.
<b>Service Support</b>	Availability of reliable after-sales support, maintenance, and training services.

Table 3: Key Criteria for Assessing Suppliers in Healthcare Device Procurement

<b>Criteria</b>	<b>Description</b>
<b>Quality Assurance</b>	Compliance with industry standards and certifications ensuring device quality.
<b>Cost-effectiveness</b>	Competitive pricing considering device features and performance.
<b>Delivery Timeliness</b>	On-time delivery and adherence to specified timelines.
<b>Warranty and Maintenance</b>	Provision of comprehensive warranty coverage and maintenance services.
<b>Technological Expertise</b>	Demonstrated proficiency and expertise in healthcare device technology.
<b>Customer Feedback</b>	Positive track record and feedback from existing clientele.
<b>Scalability</b>	Capacity to scale operations and meet future healthcare demands.
<b>Ethical Standards</b>	Adherence to ethical and regulatory standards in device manufacturing and supply.
<b>Flexibility in Customization</b>	Ability to customize devices as per specific healthcare facility requirements.
<b>Sustainability Practices</b>	Implementation of eco-friendly and sustainable manufacturing practices.

In our study, the effective evaluation of clinical devices, brands, and suppliers involves a comprehensive weighting process to ascertain the relative importance of various criteria within each category. Table 4 provides a detailed overview of the assigned weights to different criteria associated with clinical devices. These weights are derived through a meticulous assessment considering factors such as device reliability, functionality, compatibility, accuracy, and usability. The weighting process aids in establishing the significance of each criterion concerning the selection and prioritization of clinical devices within our healthcare framework, emphasizing specific attributes crucial for optimal device performance and integration.

Table 4: Weighted Criteria Assessment for Clinical Device Selection in Healthcare Procurement

	<b>C<sub>1</sub></b>	<b>C<sub>2</sub></b>	<b>C<sub>3</sub></b>	<b>C<sub>4</sub></b>	<b>C<sub>5</sub></b>
<b>BWM</b>	0.4739	0.3692	0.3623	0.2744	0.7109

<b>Ours</b>	0.5198	0.3977	0.3989	0.3811	0.7953
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Moreover, Table 5 encapsulates the weighted criteria associated with different brands of clinical devices. These weights signify the relative importance of attributes like reliability, compatibility, innovation, and service support concerning the diverse brands available in the market. The allocation of weights to brand criteria facilitates a systematic and informed decision-making process, enabling the identification of brands that align most closely with our healthcare facility's requirements and standards.

Table 5: Relative Weightings of Criteria for Brand Evaluation in Clinical Device Procurement

	<b>C<sub>1</sub></b>	<b>C<sub>2</sub></b>	<b>C<sub>3</sub></b>	<b>C<sub>4</sub></b>	<b>C<sub>5</sub></b>
<b>BWM</b>	0.8386	0.9206	0.4472	0.2525	0.8147
<b>Ours</b>	0.9259	0.9259	0.5288	0.3175	0.8160

Additionally, Table 6 represents the allocated weights for diverse supplier criteria essential for the procurement of clinical devices. These weights signify the significance of factors such as quality assurance, cost-effectiveness, delivery timeliness, technological expertise, and ethical standards in the selection of suppliers. The weighting of supplier criteria plays a pivotal role in identifying and prioritizing suppliers that meet stringent quality, reliability, and ethical benchmarks, ensuring the procurement of devices from trusted and dependable sources within our healthcare ecosystem. Overall, the detailed weighting of criteria across clinical devices, brands, and suppliers enables a nuanced assessment, guiding our decision-making process to procure devices and establish partnerships that align optimally with our healthcare objectives and standards.

Table 6: Weight Allocation for Supplier Criteria in Clinical Device Procurement

	<b>C<sub>1</sub></b>	<b>C<sub>2</sub></b>	<b>C<sub>3</sub></b>	<b>C<sub>4</sub></b>	<b>C<sub>5</sub></b>	<b>C<sub>6</sub></b>	<b>C<sub>7</sub></b>	<b>C<sub>8</sub></b>	<b>C<sub>8</sub></b>	<b>C<sub>10</sub></b>
<b>BWM</b>	0.4606	0.6322	0.4288	0.7088	0.0542	0.3745	0.1357	0.6220	0.9014	0.9646
<b>Ours</b>	0.5159	0.7157	0.4726	0.7436	0.1237	0.4071	0.2436	0.6928	0.9800	0.9083

Table 7 encapsulates the culmination of our rigorous evaluation process, presenting the comprehensive evaluation matrix derived from the weighted criteria assigned to clinical devices, brands, and suppliers within the healthcare procurement framework. This matrix serves as a consolidated repository, encompassing the amalgamation of qualitative and quantitative assessments undertaken for each criterion across clinical devices, diverse brands, and supplier selections. It synthesizes the complex data stemming from the weighted criteria, offering a systematic and structured representation of the decision-making landscape. Through this matrix, stakeholders gain invaluable insights into the relative performance, strengths, and weaknesses of various clinical devices, brands, and suppliers within the healthcare context. The evaluation matrix serves as a foundational tool, empowering informed decision-making processes by providing a holistic overview of the assessments, facilitating the identification of optimal choices aligned closely with the healthcare facility's objectives, standards, and requirements.

Table 7: Comprehensive Evaluation Matrix of Clinical Devices, Brands, and Suppliers in Healthcare Procurement"

<b>Clinical Device Type</b>	<b>C1</b>	<b>C2</b>	<b>C3</b>	<b>C4</b>	<b>C5</b>
<b>D1</b>	1	9	9	5	2
<b>D2</b>	1	10	4	6	8
<b>D3</b>	3	3	2	6	6
<b>D4</b>	9	10	10	7	10
<b>D5</b>	9	5	7	10	9

## 5. Conclusion and Future work

In conclusion, this research underscores the pivotal role of information fusion and multi-criteria decision-making in the healthcare procurement landscape, particularly in the selection of clinical devices, brands, and suppliers. By employing a systematic methodology that integrates diverse data sources from clinical devices, this study emphasizes the significance of reliability, compatibility, innovation, and quality assurance in the procurement process. The findings highlight the necessity for a structured approach that optimizes decision-making, enhances operational efficiency, and ultimately contributes to improved patient care within healthcare systems.

Looking forward, future research could focus on enhancing the dynamic adaptability of weighting methodologies by incorporating advanced analytical techniques, such as machine learning algorithms, to cater to the evolving needs of healthcare settings. Exploring the integration of emerging technologies like artificial intelligence and blockchain in supplier selection, as well as considering the environmental sustainability aspect in device procurement, holds promise for a more comprehensive understanding of sustainable healthcare practices. Moreover, the utilization of real-time data from IoT-enabled devices and predictive analytics presents an exciting opportunity to bolster the agility and responsiveness of healthcare procurement strategies. These future endeavors aim to continually advance the efficiency and effectiveness of procurement practices in healthcare, fostering innovation and meeting the evolving demands of the healthcare landscape.

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