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DEVELOPMENT OF A MATERIAL DATABASE AND AN AUTOMATED SELECTION ALGORITHM FOR A SURGICAL ROBOTIC MANIPULATOR

Abstract: Material selection for surgical robotic manipulators remains a challenging engineering problem because candidate materials must simultaneously satisfy mechanical, biomedical, environmental, manufacturing, and economic requirements. This challenge is particularly important in robotic systems for knee arthroplasty, where structural reliability and positioning accuracy strongly depend on material properties. This study presents the development of a structured component-oriented material database and an automated material selection algorithm for a collaborative surgical manipulator intended for knee joint endoprosthesis procedures. The database includes metallic materials, engineering polymers, composites, and ceramics together with their mechanical, environmental, biomedical, manufacturing, and economic characteristics. Based on this database, a multi-stage decision-support framework was developed that integrates component-specific material retrieval, hard-constraint filtering, criterion normalization, adaptive weighting, TOPSIS-based ranking, and post-ranking feasibility verification. Unlike conventional approaches that evaluate all materials simultaneously, the proposed framework retrieves only materials relevant to the selected manipulator component, reducing the search space and improving decision consistency. A numerical case study was performed for the load-bearing structure. The algorithm retrieved 21 candidate materials with complete data, of which 6 satisfied the mandatory engineering and biomedical constraints. These materials were subsequently ranked using the TOPSIS method, with AISI 316 identified as the

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most suitable material because of its balanced combination of mechanical strength, corrosion resistance, sterilization compatibility, and durability. Comparative evaluation using the SAW method produced the same three highest-ranked materials, while sensitivity analysis demonstrated that the ranking remained stable under moderate variations in weighting coefficients. The proposed framework provides a transparent, reproducible, and practically applicable approach to material selection for surgical robotic manipulators and establishes a foundation for future integration with CAD/CAE environments, intelligent decision-support systems, and machine-learning-assisted engineering design.

Keywords: surgical robotic manipulator; material selection; material database; decision support system; medical robotics.

1. Introduction

In recent decades, medical robotics has experienced rapid development and has become an integral part of modern surgical practice [1]. Robotic systems are increasingly used in minimally invasive procedures, orthopedic surgery, neurosurgery, and rehabilitation technologies [2]. One of the promising directions in this field is the development of collaborative surgical robots designed to assist surgeons during complex procedures. In particular, robotic manipulators are widely applied in orthopedic operations such as total knee arthroplasty [3].

Collaborative robotic systems used in knee replacement surgery must meet strict technical and biomedical requirements [4]. These systems operate in close interaction with surgeons and patients, which imposes additional constraints on safety, reliability, and precision. The robotic manipulator typically consists of multiple mechanical links, joints, actuators, sensors, and control electronics [5]. Each component must be manufactured from materials with carefully selected properties in order to ensure stable operation under mechanical loads and sterilization conditions.

The process of selecting suitable materials for surgical robotic manipulators is a complex engineering task. Materials must satisfy multiple criteria simultaneously, including mechanical strength, stiffness, corrosion resistance, low mass, biocompatibility, sterilization compatibility, and economic feasibility [6]. In many practical engineering situations, the selection process is performed manually by engineers based on experience and available reference data [7]. However, this approach is often time-consuming and may lead to subjective decisions. Another difficulty arises from the multidimensional nature of material properties. A single material may have high strength but excessive density, while another may be lightweight but insufficiently resistant to sterilization or corrosion. Therefore, selecting an optimal material requires simultaneous evaluation of several parameters [8]. As the number of candidate materials increases, the decision-making process becomes more complicated. Formalized digital tools capable of supporting automated material selection remain limited, particularly for medical robotic applications. This situation creates a need for systematic approaches that integrate material databases with computational selection algorithms.

The scientific contribution of this study is not limited to the use of the TOPSIS method itself, which is a well-established Multi-Criteria Decision Making (MCDM) technique. The novelty lies in the development of a component-oriented material selection framework for a surgical robotic manipulator, where mechanical, biomedical, sterilization, corrosion-resistance, manufacturability, and economic constraints are integrated into a single structured workflow. Unlike generic material selection approaches, the proposed framework distinguishes between manipulator links, joint housings, covers, drive-related elements, and tool interfaces, allowing material ranking to be adapted to the functional requirements of each component. A comparative analysis of the most commonly used multi-criteria decision-making methods, including their principal advantages and limitations in the context of engineering material selection, is presented in Table 1.

Table 1. Comparison of MCDM methods for material selection

Method	Advantages	Limitations
AHP	Useful for expert weighting	Subjective and time-consuming for many criteria
TOPSIS	Simple ranking, works with benefit and cost criteria	Sensitive to weights
VIKOR	Finds compromise solution	More complex interpretation
ELECTRE	Suitable for outranking	Less transparent for engineering users
PROMETHEE	Flexible preference modelling	Requires preference functions

TOPSIS was selected in this study because it provides a transparent numerical ranking and allows candidate materials to be evaluated according to their distance from an ideal and anti-ideal solution. This logic is suitable for early-stage material selection, where several conflicting criteria such as strength, density, corrosion resistance, sterilization compatibility, manufacturability, and cost must be considered simultaneously.

One possible solution is the development of structured material databases combined with automated algorithms capable of evaluating materials according to predefined criteria. Such systems can significantly accelerate the design process, reduce engineering uncertainty, and improve the consistency of design decisions. Structured database may serve as a foundation for future integration with intelligent design systems and machine learning methods. In the context of surgical robotics, the availability of a structured material database is particularly important. Medical devices must comply with strict regulatory standards and require materials that are not only mechanically suitable but also compatible with sterilization procedures and biological environments. Therefore, organizing material properties in a structured format can greatly facilitate the design and optimization of robotic systems. The aim of this study is to develop a structured material database and propose an automated algorithm for material selection in surgical robotic manipulators. The selection of materials for surgical robotic manipulators represents a multi-criteria engineering problem. The materials used in different components of the manipulator must satisfy mechanical, biomedical, and technological requirements. In order to automate the material selection process, these requirements must first be formalized and represented in a structured form.

Based on the above considerations, the present study addresses several interrelated research problems. First, material data required for the design of surgical robotic manipulators are fragmented across engineering handbooks, technical datasheets, standards, and scientific publications, which makes systematic comparison difficult at the early design stage. Second, general-purpose material databases are not directly organized according to the component-specific requirements of surgical robotic manipulators, where load-bearing structures, joints, housings, drive elements, and tool interfaces require different combinations of mechanical, biomedical, technological, and economic properties. Third, conventional manual material selection is strongly dependent on expert experience and may therefore lead to subjective and poorly reproducible decisions. Fourth, multi-criteria decision-making methods, including TOPSIS, are sensitive to the selected weighting coefficients; therefore, the stability of ranking results must be evaluated. Finally, a material that appears optimal according to numerical criteria may still be unsuitable in practice because of limitations related to availability, cost, manufacturability, or implementation feasibility.

Accordingly, the contribution of this study is the development of a component-oriented material selection framework that combines a structured material database, mandatory constraint filtering, criterion normalization, component-specific weighting, TOPSIS-based ranking, and post-ranking feasibility verification. In this framework, the number of candidate materials is not fixed for the whole database; instead, it depends on the selected manipulator component. For

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example, in the demonstrated case study for the load-bearing structure, 21 candidate materials were retrieved from the database, after which the feasible alternatives were filtered and ranked.

The scientific novelty of this study lies not in the standalone use of TOPSIS, but in the development of a component-oriented material selection framework for surgical robotic manipulator design. The proposed framework integrates engineering requirements, biomedical constraints, sterilization compatibility, corrosion resistance, manufacturability, economic criteria, mandatory filtering, and post-ranking feasibility verification within a single reproducible workflow.

2. Methods and Materials

2.1. Requirements for Surgical Robotic Manipulators

Robotic systems designed for orthopedic surgery, particularly for procedures such as total knee arthroplasty, must satisfy a combination of mechanical, biomedical, and operational requirements. During knee replacement surgery, the robotic manipulator assists the surgeon in positioning cutting tools and guiding surgical instruments with high precision. As a result, the materials used in the structural components of the manipulator must ensure reliable mechanical performance, resistance to environmental exposure, and compatibility with medical sterilization procedures. Unlike conventional industrial robots, surgical robotic manipulators operate in a highly controlled clinical environment where both safety and precision are critical. The manipulator must maintain stable positioning while interacting with bone tissue and surgical tools. Therefore, structural materials must possess sufficient mechanical strength to withstand operational loads and dynamic forces generated during cutting or milling processes. At the same time, high structural stiffness is required in order to minimize deflections of the tool center point (TCP) and ensure accurate positioning Another important requirement is corrosion resistance. Surgical robotic systems are frequently exposed to disinfectants, cleaning agents, and humid environments typical of operating rooms. Materials used in the construction of the manipulator must therefore resist corrosion and chemical degradation in order to maintain their structural integrity and surface quality over long-term use.

For the purpose of this study, the engineering requirements for the robotic manipulator were estimated assuming a workspace of approximately 1 m and a cutting block mass of 5 kg, which corresponds to typical configurations used in robotic systems for knee arthroplasty. These parameters are based on the characteristics of a collaborative surgical manipulator prototype currently being developed at Satbayev University for assisting surgeons during knee joint endoprosthesis procedures. Based on these design conditions, the structural components of the manipulator must withstand bending moments generated by the payload while maintaining sufficient stiffness to ensure accurate positioning of the surgical tool. The key engineering requirements derived from these conditions are summarized in Table 2.

The threshold values presented in Table 2 were established based on the functional requirements of surgical robotic manipulators and commonly accepted engineering design principles [9-11]. The minimum mechanical strength and stiffness were selected to ensure sufficient load-bearing capacity and positioning accuracy during surgical manipulation. The maximum density was limited to reduce the overall mass and inertia of the manipulator, thereby improving dynamic performance. Corrosion resistance and sterilization compatibility were considered essential because surgical robotic systems operate in clinical environments requiring repeated sterilization and long-term reliability. The specified manufacturing and durability requirements were defined to ensure practical fabrication, service life, and cost-effective implementation. These engineering thresholds were applied as preliminary screening criteria before the multi-criteria TOPSIS evaluation.

Table 2. Engineering requirements for materials used in surgical robotic manipulators designed for knee arthroplasty procedures.

Requirement category	Parameter	Typical requirement	Explanation
Mechanical strength	Maximum design moment	$\geq$ 150 N·m	Manipulator must withstand bending moment produced by a 5 kg tool at 1 m reach with safety margin
	Safety factor	$\geq$ 2.0	Ensures safe operation under dynamic surgical loads
Stiffness	TCP deflection	$\leq$ 0.5 mm under 50 N load	High stiffness ensures accurate positioning of cutting tools
	Structural stiffness	$\geq$ 100 kN/m	Required to maintain precision during bone cutting
Corrosion resistance	Corrosion rate	< 0.1 mm/year	Materials must resist disinfectants and surgical environment
	Chemical compatibility	Resistant to alcohol, peroxide and cleaning agents	Ensures long-term durability in hospital conditions
Sterilization compatibility	Temperature resistance	121–134 °C	Materials must tolerate autoclave sterilization
	Sterilization cycles	$\geq$ 100 cycles	No degradation of mechanical properties after repeated sterilization
Biomedical requirements	Surface properties	Smooth and cleanable surfaces	Prevents contamination and ensures hygienic operation
Economic requirements	Material cost	Design-dependent (e.g., < 50 $/kg for structural parts)	Ensures economic feasibility of the robotic system
	Manufacturability	CNC machining / additive manufacturing	Materials must be suitable for modern production methods

As shown in Table 2, the design requirements for surgical robotic manipulators involve several performance criteria that must be satisfied simultaneously. Mechanical strength and stiffness represent the primary structural requirements, as they directly affect the positioning accuracy and operational stability of the robotic system during surgical procedures. Environmental resistance, including corrosion resistance and chemical stability, is also essential for maintaining the durability of the manipulator when exposed to cleaning agents and disinfectants used in clinical environments. Sterilization compatibility represents another important requirement for materials used in medical robotic systems. Even if the entire robotic manipulator is not sterilized, certain components and tool interfaces may undergo repeated sterilization cycles. Therefore, the selected materials must retain their mechanical properties and structural integrity under these conditions. In addition to mechanical and biomedical requirements, economic and manufacturing considerations must also be taken into account. The selected materials must provide sufficient mechanical performance while remaining compatible with manufacturing technologies such as CNC machining or additive manufacturing. The set of requirements presented above forms the basis for the development of the structured material database described in the following section.

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These requirements are used as evaluation criteria for the automated material selection algorithm proposed in this work.

The algorithm operates in a component-oriented manner. First, the user selects the target component of the surgical robotic manipulator. Then, the system retrieves only those materials that are assigned to this component in the database. This prevents technically irrelevant materials from being included in the ranking procedure.

For example, when the load-bearing structure is selected, the algorithm analyzes materials assigned to structural parts. When reducer gears are selected, the algorithm retrieves materials suitable for gear and transmission components. Thus, the same database can support different material selection scenarios depending on the functional role of the component.

2.2. Development of the Material Database

To support automated material selection, a structured component-oriented material database was developed specifically for the design of a collaborative surgical robotic manipulator intended for knee arthroplasty. Rather than creating a generic collection of engineering materials, the database was organized according to the hierarchical structure of the robotic system.

The database consists of two interconnected datasets. The first dataset contains engineering material properties, whereas the second associates candidate materials with individual robotic components and mechanical details. This organization enables the selection algorithm to retrieve only materials relevant to the selected component before performing filtering and multi-criteria ranking.

The engineering database contains metallic materials, engineering polymers, ceramics, and composite materials commonly used in robotic systems and medical devices. For each material, mechanical, physical, biomedical, manufacturing, environmental, and economic properties were collected from engineering handbooks, material datasheets, international standards, and peer-reviewed scientific publications [12-13].

The recorded quantitative properties include density, Young's modulus, yield strength, ultimate tensile strength, hardness, ductility, fatigue resistance, impact toughness, thermal stability, and thermal expansion characteristics. Additional qualitative attributes describe corrosion resistance, biocompatibility, sterilization compatibility, chemical resistance, wear resistance, machinability, additive manufacturing compatibility, welding characteristics, service life, and relative material cost.

The second dataset represents the mechanical architecture of the robotic manipulator. Each record specifies the construction group, component, mechanical detail, and candidate materials assigned to that element. Consequently, material selection is performed separately for each manipulator component rather than across the entire material database.

To support component-oriented material selection, the developed database was organized into several interconnected entities describing both the architecture of the surgical robotic manipulator and the properties of candidate engineering materials. The database includes information on construction groups, components, individual mechanical parts, candidate materials, and their corresponding mechanical, biomedical, environmental, manufacturing, and economic characteristics. The overall structure of the developed component-oriented material database is presented in Table 3.

Table 3. Structure of the component-oriented material database

Database entity	**Description**	**Example**
Construction group	Main robotic subsystem	Load-bearing structure
Component	Mechanical assembly	Manipulator base
Detail	Individual mechanical part	Base plate
Candidate material	Engineering material assigned to the part	AISI 316
Mechanical properties	Strength, Young's modulus, hardness, density	620 MPa, 193 GPa

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Biomedical properties	Biocompatibility, sterilization compatibility	ISO-compliant
Environmental properties	Corrosion resistance, chemical stability	Excellent
Manufacturing properties	Machinability, additive manufacturing	CNC machining
Economic properties	Relative cost	USD/kg
Algorithmic role	Filtering and TOPSIS ranking	Component-specific selection

As shown in Table 3, the proposed database organization enables component-specific retrieval of candidate materials, reducing the search space and allowing only technically relevant alternatives to be processed by the subsequent filtering and TOPSIS ranking stages.

2.3. Mathematical Representation of Material Properties

To enable automated evaluation and comparison of candidate materials, the properties of each material must be represented in a structured mathematical form. Such representation allows the material selection algorithm to process multiple engineering requirements simultaneously and rank candidate materials according to their suitability for a specific robotic component.

In this study, each material is described by a vector of characteristic properties relevant to the design requirements of surgical robotic manipulators used in knee arthroplasty. These properties include mechanical, environmental, biomedical, and economic parameters derived from the engineering requirements discussed in the previous section.

The material properties can therefore be represented as a vector

$$M_i = [{}_i, E_i, \sigma_i, H_i, C_i, B_i, S_i, R_i] \tag{1}$$

where:

i = 1, 2, ..., m is the index of the candidate material, and m is the total number of candidate materials retrieved for the selected component

ρ_i– material density, which directly influences the mass and inertia of the manipulator links

E_i– Young's modulus, representing the stiffness of the material and its resistance to elastic deformation

σ_i– yield strength, indicating the maximum stress the material can withstand without permanent deformation

H_i– hardness, which is related to wear resistance of mechanical components and joints

C_i– relative material cost or economic index

B_i– biocompatibility index reflecting suitability for use in medical environments

S_i– sterilization compatibility index describing the ability of the material to withstand repeated sterilization cycles

R_i – corrosion resistance index representing stability in disinfectant and humid environments typical for operating rooms.

This vector representation enables simultaneous consideration of multiple design requirements when evaluating candidate materials. Mechanical parameters such as density, Young's modulus, and yield strength primarily influence the structural performance of the robotic manipulator, particularly its stiffness and load-bearing capacity. Environmental parameters such as corrosion resistance and sterilization compatibility ensure long-term reliability and safety of the robotic system in clinical environments.

The use of a vector-based representation also facilitates the integration of the material database with computational algorithms used for automated material selection. By normalizing these parameters and assigning appropriate weighting coefficients, it becomes possible to calculate a suitability index for each candidate material and rank materials according to their overall

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performance in the context of surgical robotic manipulators. This mathematical representation forms the basis for the automated material evaluation procedure described in the following section.

2.4 Algorithm for Automated Material Selection

After selecting the load-bearing structure, twenty-one candidate materials were retrieved automatically from the developed database. Each candidate was represented by a vector of quantitative and qualitative engineering properties, forming the initial decision matrix used in the TOPSIS procedure. The complete decision matrix is presented in Table 5.

The proposed automated material selection algorithm was developed as a structured multi-stage decision-making framework for the rational selection of engineering materials for surgical robotic manipulator components (Figure 1). The algorithm integrates database querying, constraint-based screening, multi-criteria decision analysis, and practical feasibility assessment into a unified computational pipeline. Its primary purpose is to support objective and reproducible material selection for manipulator elements operating under stringent mechanical, biomedical, technological, and economic requirements.

The architecture of the algorithm is based on the assumption that the suitability of a material for a surgical robotic component cannot be determined by a single property. Instead, material selection constitutes a multi-criteria optimization problem in which mechanical strength, stiffness, density, corrosion resistance, sterilization compatibility, manufacturability, biocompatibility, and cost must be evaluated simultaneously. To address this problem, the proposed framework employs the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which enables the ranking of candidate materials according to their relative proximity to an ideal solution and remoteness from an anti-ideal solution.

At the initial stage, the user specifies the target component of the surgical manipulator, such as a link, end-effector, housing, cover, or other structural or functional element. Based on this input, the system retrieves the corresponding subset of candidate materials from the developed material database and forms a decision matrix $X = [x_{ij}]$, where x_{ij}denotes the value of the j-th attribute for the i-th candidate material. The use of a component-oriented retrieval mechanism allows the algorithm to account for the functional role of each manipulator element and to limit the analysis to technically meaningful alternatives.

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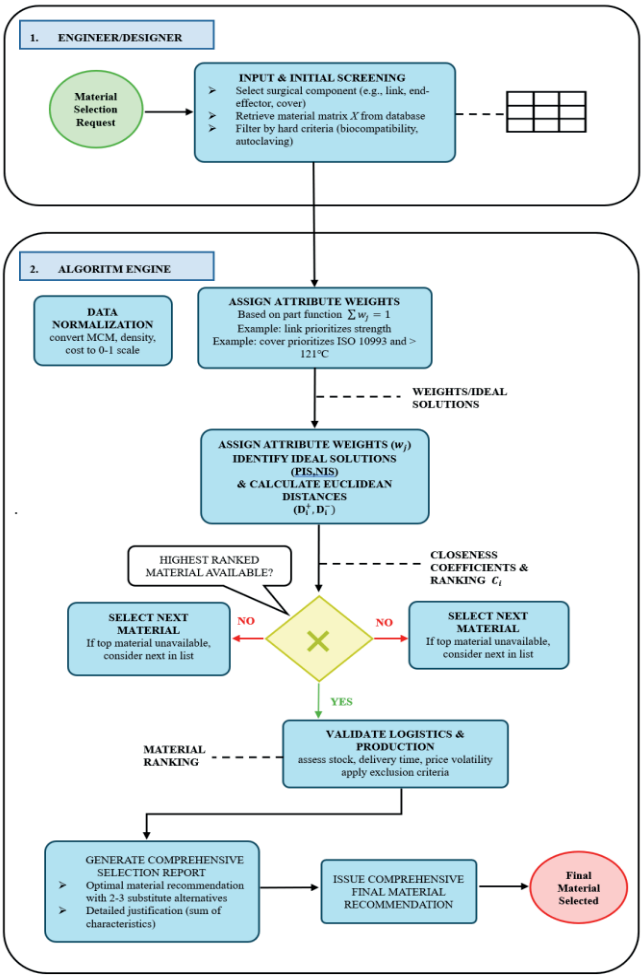

Figure 1. Algorithm for Automated Material Selection

Before the ranking procedure is performed, the algorithm applies an initial hard-constraint screening stage. This stage is essential because, in medical robotic systems, some material requirements are non-negotiable and must be satisfied prior to comparative evaluation. Such requirements may include compliance with biocompatibility standards, resistance to sterilization procedures such as autoclaving, minimum corrosion resistance in hospital environments, and threshold values for strength- or stiffness-related parameters. Any material that fails to satisfy at least one mandatory criterion is excluded from the candidate set. This preliminary filtering reduces the dimensionality of the decision problem, improves computational efficiency, and prevents infeasible alternatives from influencing the subsequent ranking results.

Since the retrieved material attributes are expressed in heterogeneous units and scales, the next stage involves normalization of the decision matrix. This transformation is required to ensure comparability among criteria with different physical meanings and numerical ranges. Let x_{ij} represent the original value of criterion j for material i. For benefit-type criteria, where higher values are preferable, the normalized value r_{ij} is calculated as

$$r_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{2}$$

For cost-type criteria, where lower values are preferable, normalization is performed according to

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VOLUME 26, JUNE 2026

$$r_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (3)$$

As a result, all criteria are transformed onto a unified dimensionless interval $[0, 1]$, where larger values consistently indicate better performance. This normalization step is particularly important for engineering datasets containing attributes such as density, yield strength, Young's modulus, hardness, cost, thermal stability, fatigue resistance, and wear characteristics.

After normalization, the algorithm performs criterion weighting in order to reflect the relative importance of material properties for the selected manipulator component. In surgical robotic systems, the significance of individual attributes depends strongly on the part function. For example, structural links require a high stiffness-to-weight ratio and sufficient fatigue resistance, whereas covers or non-load-bearing housings may prioritize sterilization stability, manufacturability, and economic efficiency. Accordingly, a weight coefficient w_j is assigned to each criterion j, subject to the normalization constraint

$$\sum_{j=1}^{n} w_j = 1 \quad (4)$$

These weights may be determined on the basis of expert judgment, engineering design requirements, literature-derived priorities, or hybrid weighting strategies [14].

In the proposed framework, weighting coefficients are not fixed for all components. Instead, the weights are assigned according to the functional role of the selected manipulator component. For load-bearing structures, higher weights are assigned to strength, stiffness, and long-term stability, while covers and housings may prioritize manufacturability, sterilization compatibility, chemical resistance, and cost. Reducer and transmission elements require higher priority for fatigue resistance and wear resistance.

Since different components of a surgical robotic manipulator perform different mechanical and functional roles, the relative importance of the evaluation criteria cannot be considered identical for all components. Therefore, component-specific weighting coefficients were assigned to reflect the engineering priorities of load-bearing structures, manipulator links, covers and housings, and reducer gears. These weighting coefficients, which satisfy the normalization condition $\sum w_i = 1$, are presented in Table 4.

Table 4. Component-Specific Weight Coefficients Used in the TOPSIS Algorithm

Criterion	Load-bearing structure	Manipulator link	Cover / housing	Reducer gear
Density	0.10	0.20	0.10	0.05
Young's modulus	0.20	0.25	0.10	0.10
Yield strength	0.20	0.15	0.10	0.20
Fatigue resistance / cyclic stability	0.15	0.10	0.05	0.20
Corrosion resistance	0.10	0.10	0.15	0.10
Sterilization compatibility	0.10	0.10	0.20	0.10
Manufacturability	0.05	0.05	0.15	0.10
Wear resistance	0.05	0.05	0.05	0.15
Cost	0.05	0.00	0.10	0.00
Total	1.00	1.00	1.00	1.00

As shown in Table 4, the weight distribution varies according to the functional role of each manipulator component. For load-bearing structures, the highest weights were assigned to Young's modulus, yield strength, and fatigue resistance because these criteria primarily determine structural rigidity and safety. For manipulator links, density and stiffness were prioritized to improve the stiffness-to-weight ratio. Covers and housings emphasize sterilization compatibility, corrosion resistance, manufacturability, and cost, whereas reducer gears prioritize yield strength, fatigue resistance, and wear resistance due to cyclic loading and contact stresses.

The weighted normalized decision matrix $V = [v_{ij}]$ is then computed as

$$v_{ij} = w_j r_{ij} \quad (5)$$

Based on this matrix, the algorithm identifies the positive ideal solution (PIS) and the negative ideal solution (NIS). The positive ideal solution corresponds to the hypothetical material exhibiting the best attainable value for each criterion, while the negative ideal solution represents the least desirable combination of criterion values. Formally, the ideal solutions are defined from the weighted normalized matrix by selecting the maximum and minimum values for each criterion, depending on its optimization direction.

For each candidate material, the Euclidean distance to the positive ideal solution and to the negative ideal solution is calculated as

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \quad (6)$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \quad (7)$$

These distance measures quantify, respectively, how far a given material is from the best possible alternative and how far it is from the worst possible alternative in the multi-criteria attribute space. The relative performance of each material is then expressed by the closeness coefficient [15-16]:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, 0 \leq C_i \leq 1. \quad (8)$$

A larger value of C_i indicates greater similarity to the positive ideal solution and, consequently, a higher overall suitability for the intended application. Candidate materials are ranked in descending order according to C_i, thereby producing a prioritized list of material alternatives for the selected manipulator component.

To improve the engineering relevance of the method, the proposed algorithm extends the classical TOPSIS ranking stage with an additional post-ranking validation module. In practical design and production environments, even a top-ranked material may be unsuitable due to supply chain limitations, manufacturing constraints, or cost instability. Therefore, the highest-ranked candidate is further evaluated in terms of logistics and implementation feasibility, including current availability, lead time, procurement risk, production compatibility, and price volatility. If the selected material fails this feasibility check, the algorithm iteratively proceeds to the next material in the ranked list until a technically and logistically viable option is found. This feature enhances the robustness of the decision-making process and aligns the algorithm with real-world requirements of surgical robotic system development.

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VOLUME 26, JUNE 2026

At the final stage, the system generates a comprehensive material selection report. This report includes the selected optimal material, the complete ranking of candidate alternatives, the corresponding closeness coefficients, and a criterion-based justification of the final decision. In addition, the report may provide two or three substitute materials with comparable performance, which is particularly useful under uncertain supply or design conditions. The reporting module increases transparency, supports traceability of engineering decisions, and facilitates expert review of the selection outcome.

The developed automated material selection algorithm represents a reproducible and scientifically grounded decision-support approach for surgical robotic manipulator design. Its novelty lies in the integration of a structured material database, mandatory constraint filtering, component-adaptive weighting, TOPSIS-based multi-criteria ranking, and post-selection feasibility validation within a single workflow. Such an approach improves the consistency, transparency, and practical applicability of material selection, while reducing the subjectivity traditionally associated with expert-driven engineering judgment. Consequently, the algorithm can serve as a reliable tool for accelerating material selection in the design and optimization of surgical robotic manipulators.

3. Results

3.1 Numerical Case Study and TOPSIS Ranking Results

To demonstrate the operation of the algorithm, the load-bearing structure was selected as a test component. For this component, the algorithm retrieved 21 candidate materials with complete data from the database. After applying mandatory constraints, 6 materials remained in the feasible candidate set. These materials were then ranked using the TOPSIS method.

After selecting the load-bearing structure, twenty-one candidate materials were automatically retrieved from the developed component-oriented material database. Each material was represented by a vector of quantitative and qualitative engineering properties, forming the initial decision matrix used as the input for the TOPSIS algorithm. Following the application of the component-specific weighting coefficients, the materials were ranked according to their relative closeness to the ideal solution. The complete decision matrix used in the case study is presented in Table 5.

Table 5. Initial Decision Matrix Used for TOPSIS Ranking

Material	Density (kg/m^3)	Young's Modulus (GPa)	Yield Strength (MPa)	Corrosion Resistance	Sterilization Compatibility	Manufacturability	Wear Resistance	Relative Cost
AISI 316	8000	193	290	5	5	5	5	2
AISI 304	7900	193	215	4	5	5	4	3
GFRP	1900	35	300	5	3	3	3	4
Al 7075-T6	2810	71.7	503	3	3	5	3	3
Al 6082-T6	2700	69	260	3	3	5	3	4
Al 6061-T6	2700	68.9	276	3	3	5	3	5

After applying the mandatory engineering and biomedical constraints, six feasible candidate materials remained for the load-bearing structure. These materials were subsequently evaluated using the TOPSIS method with the component-specific weighting coefficients described in the previous section. The resulting ranking of the feasible alternatives and their corresponding TOPSIS scores are presented in Table 6.

Table 6. TOPSIS Ranking Results for the Load-Bearing Structure

Rank	Material	TOPSIS Score	Decision
1	AISI 316	0.582178	Recommended
2	AISI 304	0.548507	Alternative
3	GFRP	0.508631	Alternative
4	7075-T6	0.475380	Conditionally suitable
5	6082-T6	0.360254	Lower priority
6	6061-T6	0.309856	Lower priority

As shown in Table 6, AISI 316 achieved the highest TOPSIS score among the screened materials. This result can be attributed to its balanced combination of corrosion resistance, mechanical strength, sterilization compatibility, and long-term durability under clinical operating conditions. AISI 304 and GFRP were identified as suitable alternative materials. In contrast, the aluminum alloys 7075-T6, 6082-T6, and 6061-T6 received lower rankings because their overall performance with respect to corrosion resistance, sterilization compatibility, and long-term durability was less favorable than that of stainless steels.

3.2 Comparative Analysis with SAW Method

To verify the robustness of the proposed material selection framework, the same set of feasible materials for the load-bearing structure was additionally evaluated using the Simple Additive Weighting (SAW) method. The objective of this comparison was not to replace TOPSIS, but to determine whether the ranking of the leading candidate materials remained consistent when another widely used MCDM method was applied. The comparative ranking results obtained using the TOPSIS and SAW methods are presented in Table 7.

Table 7. Comparison of TOPSIS and SAW Ranking Results for the Load-Bearing Structure

Rank	TOPSIS result	TOPSIS score	SAW result	SAW score
1	AISI 316	0.582178	AISI 316	0.782
2	AISI 304	0.548507	AISI 304	0.751
3	GFRP	0.508631	GFRP	0.704
4	7075-T6	0.475380	7075-T6	0.672
5	6082-T6	0.360254	6082-T6	0.581
6	6061-T6	0.309856	6061-T6	0.543

As shown in Table 7, the TOPSIS and SAW methods produced highly consistent ranking results for the load-bearing structure. In both approaches, AISI 316 was identified as the most suitable material, followed by AISI 304 and GFRP. This agreement indicates that the proposed recommendation is robust and is not dependent on a single multi-criteria decision-making method. Nevertheless, TOPSIS was adopted as the primary ranking technique because it simultaneously considers the distances to both the positive ideal and negative ideal solutions, providing a more comprehensive evaluation of candidate materials.

3.3 Sensitivity Analysis of Weight Coefficients

Since the results of multi-criteria decision-making methods may depend on the selected weighting coefficients, a sensitivity analysis was performed to evaluate the robustness of the proposed TOPSIS ranking. The weighting coefficients of the most influential criteria were

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systematically varied by ±10% and ±20%, and the resulting changes in the ranking of candidate materials were analyzed. The baseline scenario corresponded to the original weighting scheme used for the load-bearing structure. The sensitivity analysis scenarios and their corresponding ranking results are summarized in Table 8.

Table 8. Sensitivity Analysis of TOPSIS Ranking Results for the Load-Bearing Structure

Scenario	Changed criterion	Weight change	Top-1 material	Top-2 material	Ranking stability
Baseline	Original weights	-	AISI 316	AISI 304	Reference scenario
S1	Young's modulus	+10%	AISI 316	AISI 304	Stable
S2	Yield strength	+10%	AISI 316	AISI 304	Stable
S3	Corrosion resistance	+10%	AISI 316	AISI 304	Stable
S4	Sterilization compatibility	+10%	AISI 316	AISI 304	Stable
S5	Density	+20%	AISI 316	GFRP	Slight change
S6	Cost	+20%	AISI 304	AISI 316	Moderate change

As shown in Table 8, the proposed ranking remained stable under moderate variations in the most influential mechanical and biomedical criteria. AISI 316 consistently remained the highest-ranked material when the weights of Young's modulus, yield strength, corrosion resistance, and sterilization compatibility were increased by 10%, indicating that the main recommendation is robust with respect to reasonable changes in weighting assumptions. Increasing the weight assigned to density altered only the second-ranked material, replacing AISI 304 with GFRP because of the lower density of composite materials. When the weight of cost was increased by 20%, AISI 304 became the top-ranked material owing to its lower cost relative to AISI 316. Overall, the sensitivity analysis confirms the robustness of the proposed material selection framework while highlighting the importance of transparent and application-specific weight assignment in TOPSIS-based decision making.

Discussion

The main value of the proposed approach lies not in the use of a single ranking technique, but in the way the full selection process has been formalized for the specific context of a surgical robotic manipulator. In conventional engineering practice, material choice is often based on fragmented reference data and expert preference. That approach may be acceptable for simple assemblies, but it becomes less reliable when the component must simultaneously satisfy stiffness, strength, corrosion resistance, sterilization compatibility, and cost constraints, as is the case in orthopedic robotic systems. In this regard, the present study offers a more structured alternative by connecting design requirements, database organization, and algorithmic selection within one workflow. An important strength of the work is that the database was not compiled as a generic catalogue of engineering materials. Instead, it was oriented toward the functional architecture of a surgical manipulator for knee arthroplasty, including structural links, joints, drive-related elements, housings, and tool interfaces. This gives the study practical relevance, because material suitability in medical robotics is always component-dependent. A material that performs well for a non-load-bearing housing may be unsuitable for a highly stressed joint or a sterilizable tool interface. By organizing the database in this way, the authors created a foundation for more meaningful component-level decisions rather than broad and overly general recommendations.

Compared with AHP, VIKOR, ELECTRE, and PROMETHEE, TOPSIS was selected because it provides a transparent numerical ranking and can process both benefit-type and cost-type criteria [17-20]. AHP is useful for deriving expert weights but becomes cumbersome when the number of criteria increases. ELECTRE and PROMETHEE provide powerful outranking mechanisms, but their interpretation may be less straightforward for early-stage engineering design.

A potential risk of the proposed approach is erroneous material selection when the database is incomplete or contains inaccurate material properties. Therefore, the database should be continuously updated using verified datasheets, standards, and experimental results.

Future validation should include finite element analysis of selected materials in real manipulator components, mechanical testing of prototype parts, evaluation of sterilization resistance, corrosion testing, and comparison with manual material selection performed by engineering experts.

The algorithmic part of the study is also well aligned with real engineering needs. The decision to begin with hard-constraint screening is especially appropriate for medical robotic applications. In such systems, some criteria are not negotiable: if a material does not satisfy minimum sterilization compatibility, corrosion resistance, or biomechanical safety requirements, it should not remain in the candidate set merely because it scores well in another category. Only after this filtering step does comparative ranking become meaningful. This makes the proposed workflow more realistic than a purely mathematical ranking model applied to all materials without preliminary exclusion. The use of TOPSIS is justified here because the problem is inherently multi-criteria and involves both benefit-type and cost-type attributes. In the context of surgical manipulators, there is rarely a universally best material; rather, there are materials that provide a more balanced compromise for a given component. For example, titanium alloys may offer excellent corrosion resistance and biocompatibility, stainless steel may remain attractive because of its stability and manufacturability, while polymers or composites may be advantageous in lightweight secondary structures. The role of the algorithm is therefore not to produce an absolute answer, but to make those trade-offs visible and traceable. This is one of the most useful aspects of the framework developed in the article.

At the same time, the study remains a preparatory and methodological one, and this should be stated openly. The current version of the framework is based on literature-derived and handbook-based material data organized in Excel, rather than on a fully validated digital platform or on an experimentally enriched database. The ranking results therefore depend strongly on the completeness of the source data, the selected normalization strategy, and the assigned criterion weights. In practice, different experts may choose slightly different weights for structural links, covers, or end-effectors, and these choices can affect the final order of materials. This does not weaken the study; rather, it defines the next stage of work. Future development should include sensitivity analysis of weights, inclusion of experimentally measured data for locally available materials, and validation of selection outcomes against actual prototype components developed at Satbayev University. Another limitation is that material selection alone does not fully determine manipulator performance. Geometry, section design, surface treatment, manufacturing route, and assembly tolerances may influence stiffness, durability, and sterilization behavior just as strongly as the bulk material itself. For this reason, the proposed system should be viewed as an engineering decision-support tool rather than a replacement for structural analysis and prototyping. Its most realistic use is at the conceptual and early design stages, where it can narrow the field of candidates and support justified engineering choices before detailed CAD, FEA, and experimental verification are performed.

Despite these limitations, the study makes a useful contribution. It brings together a material database, a requirement-driven selection logic, and a reproducible ranking procedure in a form that is understandable both to engineers and to future developers of digital design tools. For a field such as surgical robotics, where decisions must be technically sound and well documented, that kind of formalization is already a meaningful result. The framework proposed in the article can therefore be regarded as a practical intermediate step between traditional expert-based material choice and future intelligent systems for design automation in medical robotics.

Limitations

This study has several limitations. First, the developed database is based mainly on literature, datasheets, standards, and handbook data; therefore, the ranking accuracy depends on the completeness and reliability of the collected values. Second, the weighting coefficients include expert-defined assumptions, which may influence the final TOPSIS ranking. Third, the present study provides a computational decision-support framework and does not yet include full experimental validation under real sterilization, loading, and manufacturing conditions. Finally, the proposed method is intended for early-stage material selection and should be used together with CAD modelling, finite element analysis, prototyping, and experimental testing.

Conclusion

This study addressed the problem of material selection for surgical robotic manipulators intended for knee arthroplasty by proposing a structured and practically oriented decision-support framework. The work combined three interrelated elements: formulation of engineering requirements for manipulator components, development of a material database containing mechanical, environmental, biomedical, and economic properties, and creation of an automated multi-criteria selection algorithm based on constraint filtering and TOPSIS ranking. The main outcome of the study is not simply a list of candidate materials, but a more systematic way of thinking about material selection in medical robotics. By formalizing the process, the proposed framework reduces reliance on fragmented reference data and purely subjective judgment. It also improves transparency, because each recommendation can be traced back to explicit criteria, weighting assumptions, and exclusion rules.

At the present stage, the developed database and algorithm should be viewed as a foundation rather than a finished end product. Their immediate value lies in supporting conceptual design and guiding engineers toward technically justified material choices for different manipulator components. Their longer-term value lies in the possibility of extension: the database can be expanded with experimentally measured properties, the weighting strategy can be refined for specific components, and the selection logic can later be integrated with CAD/CAE tools, digital twins, or machine learning models.

The numerical case study demonstrated that, for the load-bearing structure, the proposed algorithm retrieved 21 candidate materials from the component-oriented database and reduced them to 6 feasible alternatives after hard-constraint screening. The TOPSIS ranking identified AISI 316 as the highest-ranked material, followed by AISI 304 and GFRP. These results confirm that the developed database and algorithm can support transparent, reproducible, and component-oriented material selection for surgical robotic manipulator design.

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Data Availability Statement

The dataset supporting the findings of this study is publicly available on Zenodo at: https://doi.org/10.5281/zenodo.21488307. The repository contains the material database and supporting files used for the automated material selection framework presented in this study.

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