ACTA TECHNICA JAURINENSIS
Vol. XX, No. Y, pp. ZZ-ZZ, 2026
10.14513/actatechjaur.00789

Research Article

Optimizing Robotic Prosthetic Palm Design through Integration of LOPCOW, COBRA, and EDAS for Efficient 3D Printing Material Selection

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Submitted: 06/05/2025 Revised: 11/07/2025 Accepted: 29/09/2025 Published online: 16/01/2026

Abstract: This research presents a novel multi criteria decision making (MCDM) approach for optimizing material selection in the design of a robotic prosthetic palm, a critical component in assistive and rehabilitation technologies. The research addresses the urgent need for a systematic approach to improve material efficiency and design precision in affordable prosthetic solutions. This study uses LOPCOW to find weights and applies COBRA and EDAS methods to thoroughly evaluate and select the best 3D printing material based on their mechanical, physical, and economic properties. Key parameters such as tensile strength, elastic modulus, Poisson’s ratio, von misses stress, mass density, displacement, equivalent strain, and cost were considered in the analysis. Among the 11 material evaluated, Acrylic (MT-3) emerged as the most efficient alternative, followed by PET (MT-8) and PA Type 6(MT-5). The use of Copeland voting rule, spearman correlation (0.9364) and sensitivity analysis validated the consistency and reliability of the integrated MCDM process. This methodology not only ensures optimal material selection for enhanced prosthetic performance but also demonstrates practical potential in manufacturing application in in biomedical engineering.

Keywords: Robotic Prosthetic Palm; 3D Printing Material Optimization; LOPCOW; COBRA; EDAS

I. INTRODUCTION

The development of robotic prosthetic hands has revolutionized assistive technology, significantly improving the quality of life for individuals with upper limb amputation. These devices are designed to mimic the natural movement and functionality of a human hand, allowing users to perform daily tasks with greater ease and efficiency, by integrating sensors, actuators, and artificial intelligence (AI), modern prosthetic hands offer enhanced dexterity, grip strength, and adaptability to different surroundings.

According to Chain et al., over 2.1 million individuals in the USA are living with limb loss, with approximately 185,000 amputations occurring annually [1]. According to grand view research, global prosthetic market value is projected to grow in future which was valued at USD 1.4 billion in 2022. Technological advancement such AI, 3D printing, and biosensor will lead to more sophisticated and lifelike prosthetic hand which will enhance the dexterity and user experience. Additionally, weight consideration plays a crucial role in prosthetic design, as the average human hand weighs approximately 400 grams for men, accounting for about 0.65% of total body weight [2]. Designing prosthetic hands that closely mimic this natural weight is essential for user comfort. The above data demonstrate the growing importance and influence of robotic prosthetic hands in enhancing the lives of people with upper limb loss.

The development of a robotic prosthetic hand should be based on the material selection that would give an optimal combination of strength, softness, weight, and cost. Metals, composites, and plastics have been the materials considered in this approach to prosthetics. While aluminum and titanium will provide good strength and sharpness, they tend to be heavy and expensive; hence not so suitable for such an application where the prosthetic would need to be used over a long period. Composites would provide a fine balance between weight and strength but the complexity of their manufacturing limits their use within an economic range. However, the use of plastics has been widely popular because they are light in weight, easy to fabricate with, and cheap. For this study, plastic materials are chosen as the primary material for the robotic prosthetic palm due to their compatibility with 3D printing technology.

Since 3D printing is perfect for rapid prototyping as well as low-cost production, the prosthetic palm could be tailored for the individual user. 3D printing requires a more intricate design less material than standard fabrication, so it’s a more efficient, sustainable choice to do 3D printing. Additionally, plastics allow for adjustments to mechanical properties such as strength, flexibility, and biocompatibility to meet specific application requirements. To allow for the best selection of plastic material, a series of plastic materials are evaluated based on key mechanical and physical properties, through the application of SolidWorks CAD Modeling and Simulation tools. The selection will be based on key mechanical and physical properties that will have the most impact on performance of the prosthetic palm.

Due to the variation of mechanical properties and economic characteristics across different plastic materials used in 3D printing, selecting the most appropriate material for a robotic prosthetic palm becomes a complex decision-making problem. Attributes such as tensile strength, elastic modulus, Poisson’s Ratio, max von mises stress, mass density, resultant displacement, equivalent strain, and cost often conflict with one another, making manual selection unreliable and subjective. Therefore, a logical and systematic approach is essential to ensure an optimal balance between performance and cost. MCDM models are highly suitable for this purpose, as they enable the evaluation of alternatives against multiple, conflicting criteria in a structured and transparent manner. By applying MCDM techniques, this study ensures a more objective, data-driven, and reproducible material selection process, which is critical for the efficiency, reliability, and real-world application of 3D-printed robotic prosthetics. In this study, LOPCOW (Logarithmic Percentage Change-driven Objective Weighting) identifies how strongly each type of criterion factors into the final selection of a robotic prosthetic palm, while COBRA (Comprehensive Distance Based Ranking) and EDAS (Evaluation based on Distance from Average Solution) rank and identify the best alternative material/materials. Through the application of all of the proposed MCDM techniques above, this project can identify a high-performance, low-cost, low-mass robotic prosthetic palm using data-driven material selection in an efficient manner. The proposed framework created offers the possibility of improving higher-functioning prosthetic design overall, while improving the durability and experience of the user while using robotic prosthetic hands. Overall, the systematic approach taken can offer insight into enhancing prosthetic design and ultimately improving assistive technology and therapeutic approaches.

II. Literature Review

The development of materials for prosthetic limbs is critical to strategically mitigate the balance of performance, durability, comfort, and cost. There are so many materials available, and there is not a straightforward way to select and determine the right one that takes into account several criteria. The combination of researchers applying various materials with innovative approaches to improve prosthetic limbs moves them past traditional methods to include advances from the fields of biomechanics, neuroscience, and robotics.

The use of MCDM techniques enables the selection of decisions that is based on opposing criteria. Unlike single-objective optimization, MCDM lets one assess trade-offs between several criteria affecting a decision, hence producing a more realistic and thorough evaluation [3]. Particularly helpful in engineering, management, and social sciences where intrinsic conflicts between goals prevent the simultaneous optimization of decision variables, these techniques are most effective.

MCDM approaches are used in several different disciplines. Based on mechanical and financial factors, MCDM helps in engineering design to choose appropriate materials, components, or systems [4]. It helps assess treatment alternatives, plan hospital locations, and choose medical equipment in the healthcare industry. Environmental applications span selecting waste treatment technologies and evaluating sustainability indicators. MCDM is applied in supply chain and logistics to manage inventory, optimize routes, and choose vendors [5]. Its part has lately become vital in robotics, especially in component choice and path planning for smart systems such robotic prosthetic devices.

In MCDM, objective weighting techniques are essential as they lower biases connected to subjective methods and improve openness [6]. These methods use mathematical or statistical correlations inherent in the data to assign criteria weights. Different approaches for calculating these weights include Entropy, CRITIC, MEREC, LOPCOW and other objective approaches [7].

LOPCOW stands out among objective weighting methods due to its focus on logarithmic percentage changes, making it more responsive to meaningful deviations in data. Unlike the Entropy method, which assumes independence among criteria and is sensitive to normalization, LOPCOW offers a more balanced and assumption-free weighting approach [8]. Compared to CRITIC, which is best suited for strongly correlated criteria, LOPCOW remains effective even when such correlations are absent. While WENSLO excels in normalization, it lacks LOPCOW's fine sensitivity to percentage-based variations. MEREC evaluates the impact of removing criteria but does not emphasize proportional shifts like LOPCOW [9]. Therefore, LOPCOW is better suited for complex decision-making scenarios involving diverse criteria, such as material selection or system evaluation, where subtle data variability is crucial. Because it can objectively record intrinsic data volatility via logarithmic percentage changes, the LOPCOW technique is preferred for its great sensitivity to significant differences among several standards [10, 11]. When expert assistance is restricted, it is perfect since it lowers subjectivity in weight calculations. Being combined with ARAS and SAW methods for material handling, cobot selection, and vendor analysis, LOPCOW has shown adaptability to boost performance evaluations in Industry 4.0, manufacturing, and sustainable systems.

In MCDM, assessing and rating choices helps one to pick the best solution depending on performance against several criteria. VIKOR, MARCOS, MABAC, MAIRCA, EDAS, and COBRA offer organized frameworks for comparing different types of ranking techniques [12, 13]. Different decision-making situations call for different methods based on data qualities and problem complexity because each has different theoretical underpinnings and operational processes. To tackle difficult decision-making processes, such as selecting 3D printing materials for prosthetic designs, two complementary MCDM approaches can be used: EDAS and COBRA. COBRA combines rankings from several MCDM methods, hence reducing the impact of individual method bias and producing a consistent agreement ranking [14, 15]. This is especially helpful in prosthetic uses where several opposing performance demands including mechanical strength, cost, and biocompatibility must be assessed. Combining several approaches, COBRA guarantees that no one model controls the decision-making process, so producing a fairer and trustworthy result. In contrast of concentrating only on ideal or worst-case situations, EDAS evaluates options by their variance from the mean solution. This is especially appropriate in engineering fields where trade-offs are bound to occur. Simplicity and interpretability are also qualities of EDAS that enable decision-makers to clearly comprehend the assessment process [16]. EDAS provides more transparency in results and is less computationally demanding than techniques like VIKOR, MAIRCA, or MARCOS. Combined, COBRA and EDAS offer a strong and understandable decision-making approach suitable for material selection in prosthetic manufacture. This combined strategy improves evaluation accuracy and stays useful for real-world engineering projects.

Regarding prosthetics, Controzzi et al. reached the conclusion that interdisciplinary advancement might enable duplication of the human hand. Ultimately adding to a better user experience and prosthetic performance, better materials together with improved sensitivity, control, and durability also contribute to a more elevated user experience. They did not offer a methodical technique for choosing materials meeting such interdisciplinary demands [17]. Introducing a bio-mechatronic technique, Zollo et al. expanded on integrating several disciplines of mechanical engineering, control systems, and material choice but lacked quantitative tools to systematically compare alternative materials. Their study showed how light and adaptive structures can improve the quality of human hand movement that finally results in a more effective prosthetic [18]. Coinciding with this concept, Saikia et al. researched the biomimetic of robotics concerning prosthetic devices. They argued that optimized materials would enhance dexterity, sensory-motor representation, control, and allow amputees to engage in daily living at a higher degree, hence enhancing overall quality of life, yet the material selection standards remained qualitative and application-specific [19]. Tan et al. investigated hybrid nano-materials in addition to this information to demonstrate uses in bone, skin, and neurological optimization. Though they failed to address tradeoffs across several performance measures including durability, cost, and sensitivity [20], they explained how carbon-based, metallic and composite nano-materials can provide better bio-sensing possibilities. Rohila et al. conducted a similar investigation using ANSYS for prosthetic hand material testing concerning material testing and evaluation [21]. Rohila et al.'s findings suggested that Nylon 6 is a potential candidate for a prototype material, showing the most favorable trade-off between weight, cost, and strength. Conventional methods often fall short in capturing the full complexity of the material selection process. The application of MCDM in material selection in different application is summarized in the **Table 1** and **Table 2.**

Table 1. *Material selection using MCDM Method 1*

Sl. No.	*Author*	*Objective*	*Parameter*	*MCDM Methods*	*Finding*
1	Tayyip Koçak et al. [22]	Optimize material selection for prosthetic femurs.	12 assessment parameters, including density, tensile strength, and ultimate tensile strength and more.	PROMETHEE GAIA	Ti-6Al-7Nb, Ti-6Al-4V, and Co-Cr-W are optimal prosthetic femur materials.
2	Sultana et al. [23]	To optimize 3D printing parameters affecting PLA and ABS.	This study used parameter like infill pattern, layer thickness, infill percentage, and materials.	Taguchi-CRITIC-EDAS	PLA with 2D honeycomb, 0.10 mm layer, 50% infill showed optimal tensile performance.
3	Shahab et al. [24]	To select optimal bone scaffold materials using hybrid MCDM.	Biocompatibility-based properties of polymer and ceramic composites were used.	SWARA COPRAS	Chitosan-HA composite ranked best; natural polymers outperformed synthetics.
4	Sahoo and Choudhury [25]	Optimize material selection for a low-cost robotic wheelchair.	7 assessment parameters, including cost, mass density, tensile strength, and von mises stress and more.	CRITIC, EDAS, COPRAS	Gray cast iron is the optimal choice for a low-cost wheelchair chassis.
5	Mangera et al. [26]	To determine the optimal light metal for a paediatric prosthetic knee.	Material density, structural strength, and material cost were evaluated.	ELECTRE III	Aluminium 7175 is the optimal material for a paediatric prosthetic knee.
6	Abas et al. [27]	To select the optimal material for SAFOs using FDM.	Seven different materials were evaluated based on eleven criteria.	WISP, MARCOS, and TOPSIS, with AHP for weighting.	PLA is the best material for SAFOs, with AHP-MARCOS.
7	Bahramina and Jahan [28]	To select the optimal material for the femoral component of TKR.	Material alternatives, aseptic loosening resistance, mechanical properties, biocompatibility, and durability.	VIKOR	Porous NiTi alloy is the best material for TKR femoral components
8	Kirişci et al. [29]	To develop and apply the Fermatean fuzzy ELECTRE I method for biomaterial selection in prosthetics	Expert opinions, decision matrix, concordance, discordance, aggregation, ranking.	Fermatean fuzzy ELECTRE I.	Fermatean fuzzy ELECTRE I effectively selects optimal biomaterials for hip joint prostheses.
9	Bouraima et al. [30]	Determine sustainable healthcare devolution strategies for Kisumu County	Human resources, structure, financing, leadership, infrastructure, politics, ICT, pharmaceutical availability.	AROMAN	This study identified ICT investment and human resource development as top priority strategies.

Table 2. *Material selection using MCDM Method 2*

10	Daniyan et al. [31]	To select the optimal material and assembly method for railcar body shells using AHP analysis.	Strength-to-weight ratio, crashworthiness, mechanical properties, formability, and cost-effectiveness.	Analytical Hierarchy Process	AHP identified optimal railcar materials and assembly methods for performance and efficiency
11	Kağızman et al. [32]	To select the best thermoplastic material for CPR device chassis using MCDM method	Economic feasibility, manufacturability, sustainability, structural features, cost, durability, strength, weight, flexibility, and safety.	Intuitionistic Fuzzy (IF) TOPSIS, IF VIKOR, and IF CODAS.	PC/ABS FR is the best material for the CPR device chassis
12	Kumar and Rajak [33]	Assess and rank metallic bio-implant materials using hybrid MCDM for optimal patient outcomes	Biocompatibility, corrosion resistance, strength, density, fatigue resistance, wear resistance, elastic modulus, osseointegration, feasibility, and cost-effectiveness are key bio-implant material parameters.	SWARA AND WASPAS	Titanium-based alloys are the best choice for bio-implant applications
13	Ansaripour et al. [34]	Evaluate and rank six biomaterials for spinal TDR using MCDM methods.	Young's modulus, density, tensile strength, cost, wear rate, corrosion resistance, conductivity, toughness, strength.	Fuzzy AHP, TOPSIS, Fuzzy-VIKOR, and Fuzzy-MOORA.	ZTA and Ti–6Al–4V identified as optimal spinal disc materials
14	Du et al. [35]	Develop biocompatible Ti-Zr-Si BMG for bio-implants using mechanical alloying and SPS.	Biocompatibility, porosity, compression strength, Young's modulus, density, corrosion resistance, hardness, wear resistance, manufacturability, cost-effectiveness.	AHP	Biocompatible Ti-Zr-Si BMG shows ideal strength and modulus for bio-implants
15	Rouhani Tazangi [36]	To assess hospital e-procurement readiness	People, Management, Environment, Technology, Process	GRA	Management support and technological infrastructure are key drivers of e-procurement readiness.

1. Research Gap of the Study

Despite the growing interest in robotic prosthetics, there remain several key research gaps in material selection methodologies for 3D-printed prosthetic palms:

i. Lack of a systematic decision-making framework. Existing studies do not provide a structured approach to evaluating plastic materials specifically for prosthetic palm applications.

ii. Limited exploration of advanced MCDM techniques – While AHP, TOPSIS, and VIKOR are commonly used in material selection, they have limitations in handling complex trade-offs between different criteria. There is little research integrating LOPCOW, COBRA, and EDAS for optimized material selection in prosthetic designs.

iii. Insufficient focus on 3D-printed plastic materials – Most studies focus on metals and composite materials, neglecting the potential of plastic-based prosthetic palms, which offer lightweight, cost-effective, and customizable solutions. The role of 3D printing in prosthetic development has not been extensively explored in conjunction with advanced MCDM techniques.

2. Novelty of the Study

The development of robotic prosthetic palms has significantly advanced with improvements in sensor integration, artificial intelligence, and additive manufacturing techniques. However, selecting an optimal material remains a crucial challenge, impacting factors such as durability, flexibility, lightweight properties, and cost-effectiveness. While numerous studies have explored material selection using traditional methods, this research introduces a decision-making approach by integrating LOPCOW, COBRA, and EDAS to systematically identify the most suitable plastic material for 3D-printed prosthetic palms.

Moreover, this research utilizes finite element analysis (or FEA) in SolidWorks, which allows for a more data-driven, performance based assessment of different plastic materials. FEA considers the key mechanical properties of tension strength, elastic modulus, Poisson's ratio, shear modulus, von Mises stress, mass density, resultant displacement, equivalent strain and cost to ensure the chosen material is viable as an economically structurally sound prosthetic palm.

3. Key Parameters for Material Selection in Artificial Robotic Prosthetic limb

Selecting an optimal material for an artificial robotic prosthetic palm requires a careful evaluation of several mechanical, physical, and economic parameters to ensure durability, flexibility, and cost-effectiveness. The following key parameters play a crucial role in determining the most suitable plastic material for a 3D-printed prosthetic palm:

i. Tensile Strength (TS) – The ability of a material to sustain pulling forces until failure. The higher the tensile strength of the prosthetic palm, the longer the prosthetic palm would retain its structural integrity after everyday tasks [37].

ii. Elastic Modulus (EM) – The amount of stiffness of the material and the ability to return to its original shape after being deformed. Appropriate elastic modulus of the material allows the prosthetic palm to show flexibility and rigidity in certain applications [38].

iii. Poisson's Ratio (PR) – How much a material distorts in a direction plane perpendicular to the direction of the stress. A balance of Poisson's ratio allows the selected material to optimally distribute stress without excess distortion [39].

iv. Von Mises Stress (VON) – Evaluates the maximum stress a material can withstand before failure. This property illustrates how well the material can take large forces and loads in the real world without experiencing structural failure [40].

v. Mass Density (MD) – Considering the mass density is also important to the overall weight of the prosthetic palm. As user comfort is a major concern, appropriate mass density of the plastic material is needed to closely represent the weight of a human hand while allowing realistic movement [41].

vi. Resultant Displacement (RD) – This measures the maximum deformation of the material when subject to a load. A low resultant displacement indicates that the material returns to its shape under load and will hold up over the long term [42].

vii. Equivalent Strain (ES) – This indicates where the strain is found in the material. Helping to show where the areas of deformation typically happen. We do not like to think of deformation when optimising design, but it is good to know where the weakest areas are, so that we can improve them [43].

viii. Cost (CO) – This helps ascertain if the material can be used economically to manufacture in large volumes. We want to achieve a compromise between performance, and cost to make the prosthetic palm affordable to the user without compromising quality [44].

This work have used SolidWorks CAD modeling and simulation software to optimize the above parameters to apply MCDM for selection of Plastic material that to be used for optimal design of Robotic Prosthetic Palm.

4. Objective of this study

The objective of this research is to improve the material selection process for a plastic based robotic prosthetic palm by combining LOPCOW, COBRA and EDAS MCDM approaches.

The study aims to achieve the following specific objectives:

i. To identify and evaluate suitable materials (plastics) for the fabrication of a robotic prosthetic palm, considering their mechanical, physical, and economic properties.

ii. To utilize SolidWorks CAD modeling and simulation to analyze key material properties

iii. To implement LOPCOW for determining the relative importance of different material selection criteria in an objective manner.

iv. To apply COBRA and EDAS to rank and select the best plastic material based on its overall performance across multiple criteria.

v. To perform a sensitivity analysis on the result derive from applied MCDM methods.

vi. To provide insights for future research and practical applications in prosthetic development and material selection methodologies, contributing to advancements in assistive robotics and biomedical engineering.

By achieving these objectives, the study aims to enhance the efficiency, affordability, and functionality of robotic prosthetic palms, ultimately improving the quality of life for individuals with upper limb amputations.

III. Methodology

The methodology adopted in this study follows a systematic approach to optimize the material selection process for a plastic-based robotic prosthetic palm as shown in **Fig. 1**.

The process includes criteria assessment through structural analysis, objective weighting using LOPCOW, and alternative ranking using COBRA and EDAS. Finally, Copeland's rule is employed to determine the ultimate ranking, and sensitivity analysis is performed to validate the results.

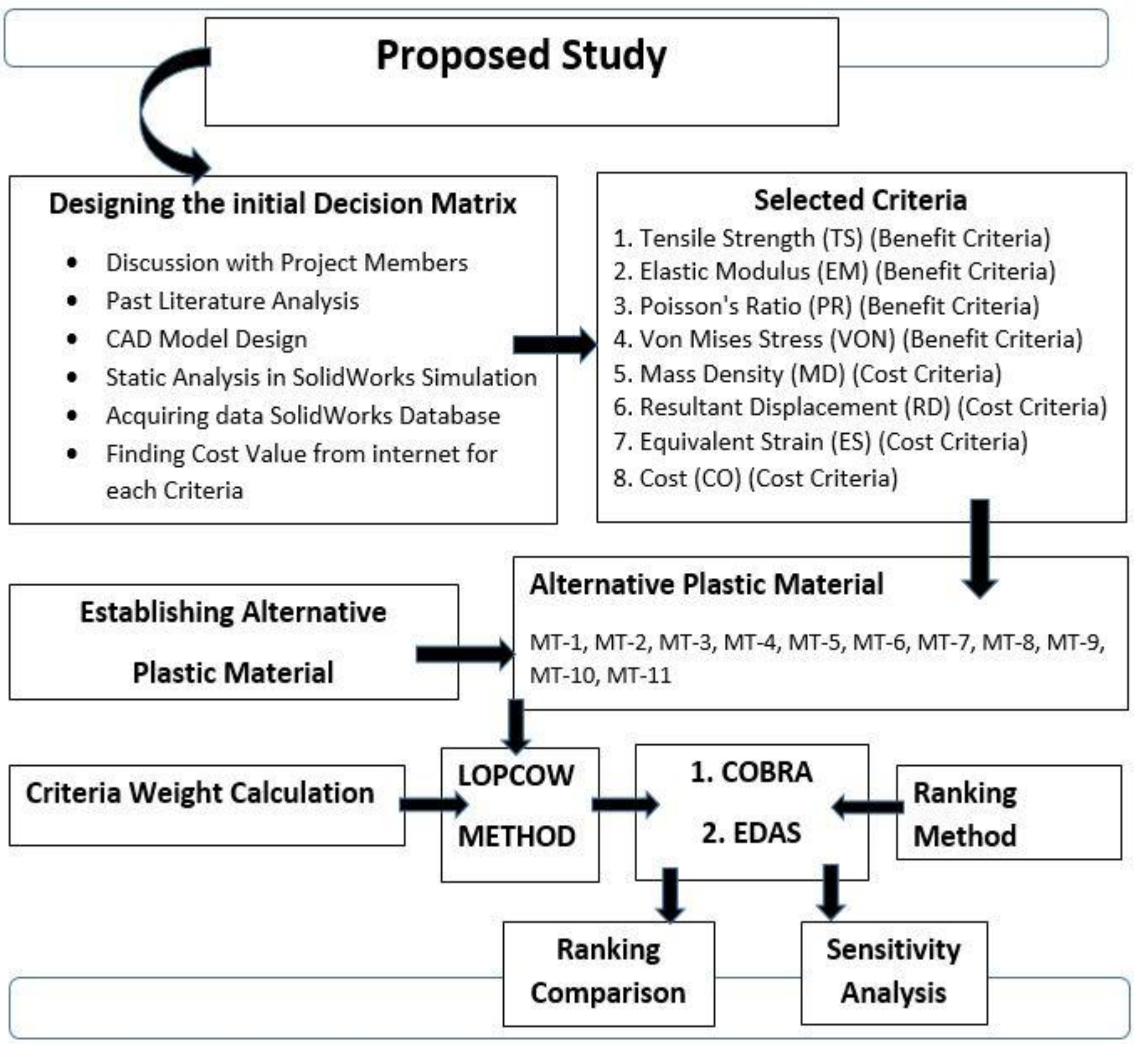


Figure 1. *Framework of the presented Study*

1. Criteria Assessment through Structural Analysis

Structural analysis is a crucial step in prototype design, as it ensures the safety, stability, and performance of the structure under expected loads and conditions [45, 46, 47]. To ensure an optimal prosthetic palm design, this study began by analyzing the natural human palm's dimensions, which were measured and documented as shown in **Fig. 2** (A, B and C). These measurements served as the foundation for constructing a precise 3D CAD model in SolidWorks. The model was designed to closely replicate the natural structure and functional aspects of a human palm, allowing for an accurate structural analysis of different plastic materials.

From the SolidWorks material database, an initial selection of 16 plastic materials was considered for evaluation. However, five materials were excluded due to their unsuitability for 3D printing. These included Epoxy, Delrin 2700, PEEK, Plasticized PVC 0.007, and Nylon 610, as they either required specialized printing conditions, exhibited excessive flexibility, or were primarily used for coatings rather than structural applications.

After filtering out these materials, 11 plastic materials were shortlisted for further analysis, including ABS PC (MT-1), ABS (MT-2), Acrylic (MT-3), Nylon 101 (MT-4), PA Type 6 (MT-5), PC High Viscosity (MT-6), PE High Density (MT-7), PET (MT-8), POM Acetal Copolymer (MT-9), PP Copolymer (MT-10), and PVC Rigid (MT-11).

For each selected material, a static analysis was performed using the SolidWorks simulation module, applying a 10 Newton force to the CAD model to assess the mechanical response as shown in **Table 3**. The analysis focused on key parameters essential for material selection, including Max von Mises Stress, Resultant Displacement (MAX), and Equivalent Strain. These parameters provided insights into the structural integrity, and deformation characteristics of each material, ensuring that the prosthetic palm could withstand real-world forces while maintaining flexibility and durability.

The results from the static analysis for all 11 materials were systematically recorded in **Table 4**, allowing for comparative evaluation. This data serves as the foundation for MCDM process, where LOPCOW, COBRA, and EDAS methods will be employed to determine the most suitable material for the prosthetic palm.

2. Logarithmic Percentage Change-driven Objective Weighting (LOPCOW)

In order to solve MCDM problems, criteria weighting is essential. The ultimate ranking and decision results are directly impacted by the methodology employed to assess each criterion's significance [48]. Due to its significance, different aspects of weighing methods have been studied in depth by several contributory researchers [49, 50]. The objective weighting method in question within this study is LOPCOW method developed at first in article by Ecer and Pamucar [51]. The LOPCOW method has some advantages, as the setting of the negative values in the initial decision matrix is often problematic in the practical applications [52]. Furthermore, this method applies log operations in order to mitigate the effect of extremes in datasets [53].

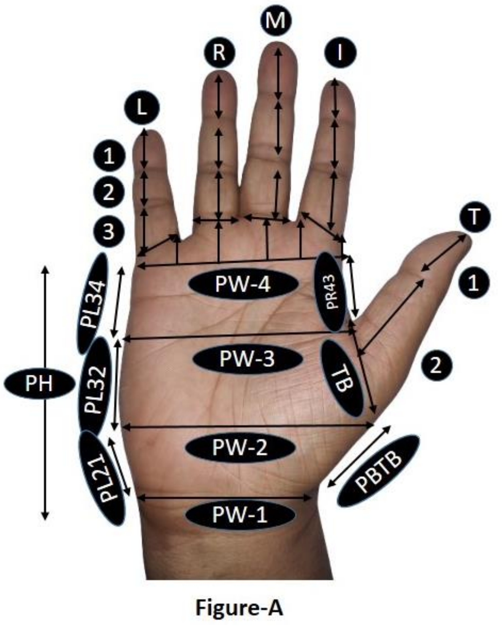


Figure-A

Finger Dimensions	1 (mm)	2 (mm)	3 (mm)	Base (mm)	Base to PW-4
THUMB (T)	34	36	-	45	-
INDEX (I)	25	25	25	23	16,5
MIDDLE (M)	26	28	30	21	18
RING (R)	26	26	26	21	15
LITTLE (L)	24	20	20	21	9

Figure-B

Palm Dimensions	In mm
Palm Width (PW)-1	65
Palm Width (PW)-2	93
Palm Width (PW)-3	95
Palm Width (PW)-4	90
Palm Left (PL)-21	20
Palm Left (PL)-32	38
Palm Left (PL)-34	37
Palm Right (PR)-43	30
Palm Base Thumb Base (PBTB)	40
Palm Height (PH)	95

Figure-C

Figure 2. *Dimension of different parts of hand*

Table 3. *SOLIDWORK Simulation of three sample materials*

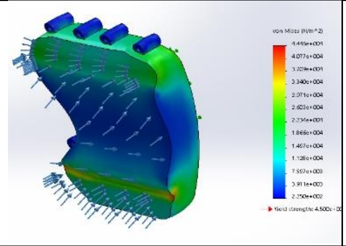
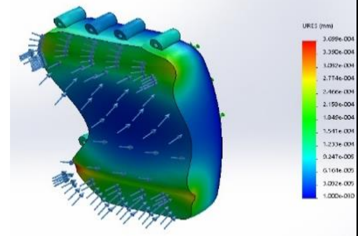
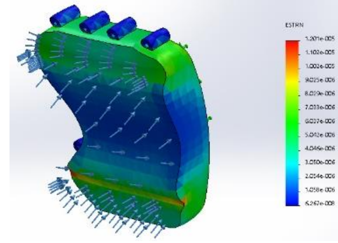
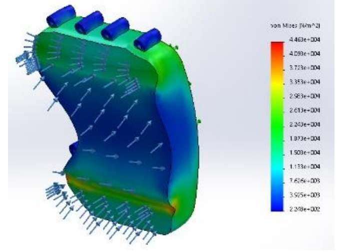
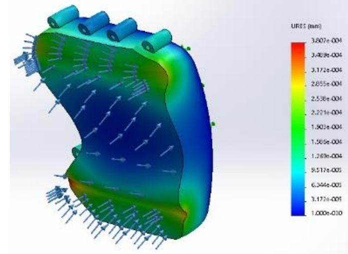
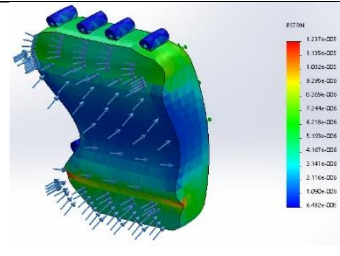
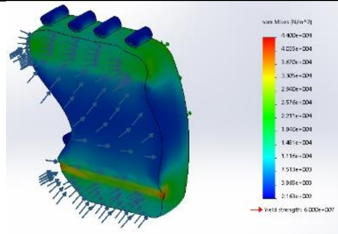
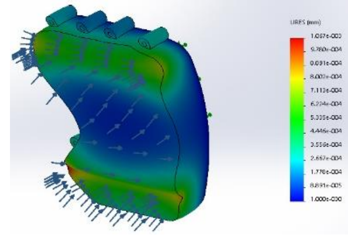
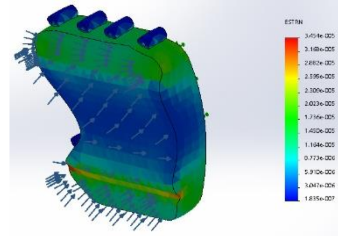
Material	Von Mises Stress	Resultant Displacement	Equivalent Strain
Acrylic (MT-3)			
PET (MT-8)			
Nylon 101 (MT-4)			

Table 4. *Criteria assessment for presented study*

Material	***TS in 10^7 N/m^2***	***EM in 10^9 N/m^2***	***PR***	***VON in 10^4 N/m^2***	***MD in kg/m^3***	***RD in 10^4 mm***	***ES in 10^5***	***CO in $ per KG***
MT-1	4.00	2.41	0.39	4.48	1070	4.75	1.54	2.5
MT-2	3.00	2.00	0.39	4.48	1020	5.74	1.87	4.5
MT-3	7.30	3.00	0.35	4.45	1200	3.70	1.20	3.5
MT-4	7.93	1.00	0.30	4.4	1150	10.70	3.45	5.5
MT-5	9.00	2.62	0.34	4.44	1120	4.20	1.36	5.0
MT-6	6.27	2.32	0.39	4.48	1190	4.94	1.60	6.0
MT-7	2.21	1.07	0.41	4.49	952	10.9	3.53	2.0
MT-8	5.73	2.96	0.37	4.46	1420	3.81	1.24	2.5
MT-9	7.15	2.6	0.39	4.48	1390	4.39	1.43	9.0
MT-10	2.76	0.89	0.41	4.49	890	13.00	4.21	2.5
MT-11	4.07	2.41	0.38	4.47	1300	4.72	1.53	2.0

It also differentiates between cost and benefit criteria taking into account differences in the scales of the measurements via percent calculations of the data's mean square and standard deviation. Another significant strength is that LOPCOW is efficient in analysing large datasets [54]. To calculate the importance weight of each criterion, LOPCOW follows these steps.

Step 1: Construct the Initial Decision Matrix

The methodology starts from an original decision matrix (L), which is given in the following form:

$$L = \begin{bmatrix} L_{11} L_{12} \dots L_{1n} \\ L_{21} L_{22} \dots L_{2n} \\ . \quad . \quad \dots \quad . \\ L_{m1} L_{m2} \dots L_{mn} \end{bmatrix} \tag{1}$$

Step 2: Normalize the Decision Matrix

The objective data is normalized to a non-dimensional interval [0, 1] in order that the different criteria are equivalent according to Eq. (2 and 3). The normalization is also differently applied according to the type of criterion chosen (cost or benefit):

- For beneficial criteria, normalization is performed using:

$$n_{ij} = \frac{L_{ij} - L_{min}}{L_{max} - L_{min}} \tag{2}$$

- For cost-based criteria, normalization is performed using:

$$n_{ij} = \frac{L_{max} - L_{ij}}{L_{max} - L_{min}} \tag{3}$$

Step 3: Compute the Percentage Value (PV)

The PV for each criterion, indicating its significance, is determined. The method requires the set of Normalized values (n_{ij}), Standard deviation (σ) of the criterion and Number of alternatives (m). The PV is calculated with Equation 4.

$$PV_{ij} = \left| \ln\left(\frac{\sqrt{\sum_{i=1}^{m} n_{ij}^2}}{m\sigma}\right) \times 100 \right| \tag{4}$$

Step 4: Determine the Criteria Weights

In the final step, the weight (w_j) of each criterion is calculated by normalizing the PV values using Equation 5.

$$w_j = \frac{PV_{ij}}{\sum_{i=1}^{n} PV_{ij}} \tag{5}$$

This method guarantees that the more significant criteria are weighted more heavily, which makes for a fairer and more realistic evaluation process.

3. Comprehensive Distance Based Ranking (COBRA)

Since its introduction by Krstić et al. [55], the COBRA method has been fairly recent, and its full potential has not yet been fully realized. It has only been mentioned in a small number of research articles thus far, most of which concentrate on its use in supply chain management practices [56, 57]. A series of steps can be used to methodically describe the COBRA method's computational procedure.

Step 1: Construct the Decision Matrix

The procedure outlined in section 3.2 (step-1) is followed in this stage.

Step 2: Normalize the Decision Matrix

To standardize the values, the decision matrix (L) is transformed into a normalized decision matrix using Equation 6. This ensures that all criteria are scaled proportionally within a common range.

$$nl_{ij} = \frac{L_{ij}}{max_i L_{ij}} \tag{6}$$

Step 3: Compute the Weighted Normalized Decision Matrix

The normalized values (nl_{ij}) are weighted according to the relative importance w_j of each criterion, forming the weighted normalized matrix (wnl_{ij}) using Equation 7.

$$wnl_{ij} = \left[w_j \times nl_{ij}\right]_{n\times m} \tag{7}$$

Step 4: Identify Key Solutions (Ideal, Negative, and Average Solutions)

For each criterion, determine three key reference points:

- Positive Ideal Solution (PIS):

$$PIS_j = max_j\left(w_j \times nl_{ij}\right) \quad \text{For benefit cri.} \tag{8}$$

$$PIS_j = min_j\left(w_j \times nl_{ij}\right) \quad \text{For cost cri.} \tag{9}$$

- Negative Ideal Solution (NIS):

$$NIS_j = min_i\left(w_j \times nl_{ij}\right) \quad \text{For benefit cri.} \tag{10}$$

$$NIS_j = max_i\left(w_j \times nl_{ij}\right) \quad \text{For cost cri.} \tag{11}$$

- Average Solution (AS):

$$AS_j = \frac{\sum_{i=1}^{n}\left(w_j \times nl_{ij}\right)}{n} \tag{12}$$

Step 5: Calculate Distances from Key Solutions

For each alternative, compute the distances from PIS, NIS, and AS using the Equation 13 and 14.

- Generalized Distance Formula:

$$d(S_j) = dE(S_j) + \{\sigma \times dE(S_j) \times dT(S_j)\} \tag{13}$$

$$\sigma = max_i dE(S_j)_i - min_i dE(S_j)_i \tag{14}$$

Where, the correction coefficient is denoted by σ and distance solution $d(S_j)$ using Euclidean $dE(S_j)$ and Taxicab distance $dT(S_j)$.

- Euclidean distance calculation from PIS, NIS, and positive distance from the average solution $(AS_j)_i^+$, negative distance from the average solution$(AS_j)_i^-$, adjustment factors (τ^+) and (τ^-) using Equation 15 to 20.

$$dE(PIS_j)_i = \sqrt{\sum_{j=1}^{m}\left(PIS_j - w_j \times nl_{ij}\right)^2} \tag{15}$$

$$dE(NIS_j)_i = \sqrt{\sum_{j=1}^{m}\left(NIS_j - w_j \times nl_{ij}\right)^2} \tag{16}$$

$$dE(AS_j)_i^+ = \sqrt{\sum_{j=1}^{m}\tau^+\left(AS_j - w_j \times nl_{ij}\right)^2} \tag{17}$$

$$dE(AS_j)_i^- = \sqrt{\sum_{j=1}^{m} \tau^-(AS_j - w_j \times nl_{ij})^2} \tag{18}$$

$$\tau^+ = \begin{cases} 1 \; if \; AS_j < w_j \times nl_{ij} \\ 0 \; if \; AS_j > w_j \times nl_{ij} \end{cases} \tag{19}$$

$$\tau^- = \begin{cases} 1 \; if \; AS_j > w_j \times nl_{ij} \\ 0 \; if \; AS_j < w_j \times nl_{ij} \end{cases} \tag{20}$$

- Taxicab distance calculation from PIS, NIS, and positive distance from the average solution$(AS_j)_i^+$, negative distance from the average solution$(AS_j)_i^-$ using Equation 15 to 20.

$$dT(PIS_j)_i = \sum_{j=1}^{m} |PIS_j - w_j \times nl_{ij}| \tag{21}$$

$$dT(NIS_j)_i = \sum_{j=1}^{m} |NIS_j - w_j \times nl_{ij}| \tag{22}$$

$$dT(AS_j)_i^+ = \sum_{j=1}^{m} \tau^+|AS_j - w_j \times nl_{ij}| \tag{23}$$

$$dT(AS_j)_i^- = \sum_{j=1}^{m} \tau^-|AS_j - w_j \times nl_{ij}| \tag{24}$$

Step 6: Compute the Final Ranking

The comprehensive distance (dC_i) for each alternative is obtained using Equation 25. Finally, the alternatives are ranked in ascending order of (dC_i), with the lowest value representing the best alternative.

$$dC_i = \frac{d(PIS_j)_i - d(NIS_j)_i - d(AS_j)_i^+ + d(AS_j)_i^-}{4} \tag{25}$$

4. Evaluation based on Distance from Average Solution (EDAS)

EDAS is a successful MCDM method for solving complex decision-making problems in the presence of many attributes [58]. This delineation considers alternatives by assessing their separation from an average solution in a multi-dimensional parameter space. The EDAS takes into account both Positive Distance from Average (PDA) and Negative Distance from Average (NDA) in order to generate a proper ranking of alternatives. The EDAS algorithmic steps are as follows:

Step 1: Construct the Decision Matrix

The process as presented (LOPCOW step-1) is employed in this step.

Step 2: Compute the Average Value of Each Criterion

Second step is to estimate the average score for each criteria using Eq. (26).

$$AVG_j = \frac{\sum_{i=1}^{m} L_{ij}}{m} \tag{26}$$

Where, AVG_j is the mean value of the criterion for all alternatives.

Step 3: Determine PDA and NDA for Each Alternative

Depending on whether the criterion is a benefit or a cost, PDA and NDA values are calculated using the following equations:

- **For a Benefit Criterion:**

$$PDA_{ij} = \frac{max\left(0, (L_{ij} - AVG_j)\right)}{AVG_j} \tag{27}$$

$$NDA_{ij} = \frac{max\left(0, (AVG_j - L_{ij})\right)}{AVG_j} \tag{28}$$

- **For a Cost Criterion:**

$$PDA_{ij} = \frac{max\left(0, (AVG_j - L_{ij})\right)}{AVG_j} \tag{29}$$

$$NDA_{ij} = \frac{max\left(0, (L_{ij} - AVG_j)\right)}{AVG_j} \tag{30}$$

Step 4: Compute the Weighted Sum of PDA and NDA

For each alternative, the weighted sum of PDA and NDA is determined using equation 31 and 32:

$$WSP_i = \sum_{j=1}^{n} w_j \, PDA_{ij} \tag{31}$$

$$WSN_i = \sum_{j=1}^{n} w_j \, NDA_{ij} \tag{32}$$

Where, w_j is the weight assigned to the j_{th} criterion.

Step 5: Normalize PDA and NDA Scores

The normalization of PDA and NDA values for each alternative is performed using equation 33 and 34:

$$NWSP_i = \frac{WSP_i}{max_i(WSP_i)} \tag{33}$$

$$NWSN_i = 1 - \frac{WSN_i}{max_i(WSN_i)} \tag{34}$$

Step 6: Compute the Final Appraisal Score

The overall evaluation score (FAS_i) for each alternative is calculated using:

$$FAS_i = \frac{1}{2}(NWSP_i + NWSN_i) \quad (35)$$

Where, FSA_i values range between 0 to 1.

Step 7: Rank the Alternatives

Finally, all alternatives are ranked in descending order based on their appraisal scores (FAS_i). The alternative with the highest FAS_i is considered the best choice.

IV. Result and Analysis

This section includes illustrative case studies that validate and demonstrate the practical implementation of the proposed study.

1. Application of the LOPCOW Method

The LOPCOW method is applied in the first phase of the decision-making process to determine the weight of criteria for the selected materials. Initially, the normalized decision matrix is constructed using Equation 2 and 3 as shown in **Table 5**. Then, the comprehensive weights derived percentage value. The LOPCOW method calculates the percentage value of each criteria using standard deviation using Equation 3 and 4 as shown in **Table 6** This systematic approach ensures different criteria weight for prosthetic palm.

In optimizing the robotic prosthetic palm design using LOPCOW, the most significant criteria are Resultant Displacement (0.1417), Equivalent Strain (0.1416), and Max von Mises Stress (0.1400), indicating that mechanical performance is crucial. Poisson's Ratio (0.1307) and Elastic Modulus (0.1191) also contribute notably. Cost (0.1364) and mass Density (0.0967) are moderately important, balancing efficiency and material use. Tensile Strength (0.0938) has the least impact.

Table 5. *Normalization of the Decision-Matrix*

Material	*TS*	*EM*	*PR*	*VON*	*MD*	*RD*	*ES*	*CO*
MT-1	0.2636	0.7204	0.8132	0.8889	0.6604	0.8871	0.8870	0.9286
MT-2	0.1163	0.5261	0.8522	0.8889	0.7547	0.7806	0.7774	0.6429
MT-3	0.7496	1.0000	0.4533	0.5556	0.4151	1.0000	1.0000	0.7857
MT-4	0.8424	0.0521	0.0000	0.0000	0.5094	0.2473	0.2525	0.5000
MT-5	1.0000	0.8199	0.3626	0.4444	0.5660	0.9462	0.9468	0.5714
MT-6	0.5979	0.6777	0.8268	0.8889	0.4340	0.8667	0.8671	0.4286
MT-7	0.0000	0.0853	0.9982	1.0000	0.8830	0.2258	0.2259	1.0000
MT-8	0.5184	0.9810	0.6346	0.6667	0.0000	0.9882	0.9867	0.9286
MT-9	0.7275	0.8104	0.7788	0.8889	0.0566	0.9258	0.9236	0.0000
MT-10	0.0810	0.0000	1.0000	1.0000	1.0000	0.0000	0.0000	0.9286
MT-11	0.2739	0.7204	0.7480	0.7778	0.2264	0.8903	0.8904	1.0000

Table 6. *Percentage Value and weights of selected criteria*

Material	*TS*	*EM*	*PR*	*VON*	*MD*	*RD*	*ES*	*CO*
MT-1	0.0695	0.5189	0.6614	0.7901	0.4361	0.7869	0.7868	0.8622
MT-2	0.0135	0.2767	0.7263	0.7901	0.5696	0.6094	0.6044	0.4133
MT-3	0.5619	1.0000	0.2055	0.3086	0.1723	1.0000	1.0000	0.6173
MT-4	0.7097	0.0027	0.0000	0.0000	0.2595	0.0612	0.0638	0.2500
MT-5	1.0000	0.6722	0.1315	0.1975	0.3204	0.8954	0.8965	0.3265
MT-6	0.3575	0.4593	0.6837	0.7901	0.1883	0.7511	0.7519	0.1837
MT-7	0.0000	0.0073	0.9964	1.0000	0.7797	0.0510	0.0510	1.0000
MT-8	0.2687	0.9624	0.4028	0.4444	0.0000	0.9765	0.9736	0.8622
MT-9	0.5293	0.6568	0.6065	0.7901	0.0032	0.8571	0.8530	0.0000
MT-10	0.0066	0.0000	1.0000	1.0000	1.0000	0.0000	0.0000	0.8622
MT-11	0.0750	0.5189	0.5594	0.6049	0.0513	0.7927	0.7928	1.0000
SUM	3.5918	5.0754	5.9734	6.7160	3.7804	6.7812	6.7738	6.3776
σ	0.9960	1.3754	1.5987	1.7905	1.0396	1.8175	1.8154	1.7083
P_j	55.5562	70.5490	77.4497	82.9198	57.2853	83.9327	83.8737	80.8045
W_j	0.0938	0.1191	0.1307	0.1400	0.0967	0.1417	0.1416	0.1364

2. Application of the COBRA Method

This study applies the COBRA method to rank 11 alternative materials based on multiple criteria. The process includes constructing and normalizing the decision matrix, applying criterion weights, identifying key reference solutions, and calculating generalized distances using Equation 6 to 25 and the corresponding values are included in **Table 7 to 9**. The final rankings are derived from comprehensive distance values, offering a structured and accurate multi-criteria decision-making approach as shown in **Table 10**.

The approach of COBRA was utilized and eleven materials were ranked for optimal design. COBRA method presents that acrylic (MT-3), PET (MT-8), and PA type 6 (MT-5) are the most appropriate materials since lower comprehensive distances (DC) are obtained. Such materials as Nylon 101 (MT-4) and PP Copolymer (MT-10) were rated as the least suitable on account of the relatively large DC values. This methodology provides the objective, empirical criteria for choosing 3D printing materials that will improve functionality and performance of the prosthesis.

Table 7. *Weighted Normalization of the Decision-Matrix*

Material	***TS***	***EM***	***PR***	***VON***	***MD***	***RD***	***ES***	***CO***
MT-1	0.0417	0.0957	0.1242	0.1397	0.0729	0.0518	0.0518	0.0379
MT-2	0.0313	0.0794	0.1256	0.1397	0.0695	0.0626	0.0629	0.0682
MT-3	0.0761	0.1191	0.1115	0.1387	0.0817	0.0403	0.0404	0.0530
MT-4	0.0826	0.0397	0.0956	0.1372	0.0783	0.1166	0.1160	0.0834
MT-5	0.0938	0.1040	0.1083	0.1384	0.0763	0.0458	0.0457	0.0758
MT-6	0.0653	0.0921	0.1247	0.1397	0.0810	0.0538	0.0538	0.0909
MT-7	0.0230	0.0425	0.1307	0.1400	0.0648	0.1188	0.1187	0.0303
MT-8	0.0597	0.1175	0.1179	0.1390	0.0967	0.0415	0.0417	0.0379
MT-9	0.0745	0.1032	0.1230	0.1397	0.0947	0.0478	0.0481	0.1364
MT-10	0.0288	0.0353	0.1307	0.1400	0.0606	0.1417	0.1416	0.0379
MT-11	0.0424	0.0957	0.1219	0.1394	0.0885	0.0514	0.0515	0.0303
PIS	0.0938	0.1191	0.1307	0.1400	0.0606	0.0403	0.0404	0.0303
NIS	0.0230	0.0353	0.0956	0.1372	0.0967	0.1417	0.1416	0.1364
AS	0.0563	0.0840	0.1195	0.1392	0.0786	0.0702	0.0702	0.0620

Table 8. *Distances from Positive and Negative Ideal Solution*

	Distances from Positive Ideal Solution d(PIS)				***Distances from Negative Ideal Solution d(NIS)***			
Material	dE(PIS)	dT(PIS)	σ(PIS)	d(PIS)	dE(NIS)	dT(NIS)	σ(NIS)	d(NIS)
MT-1	0.0614	0.1251	0.0964	0.0622	0.1767	0.4121	0.1063	0.1845
MT-2	0.0896	0.1992	0.0964	0.0913	0.1441	0.3380	0.1063	0.1493
MT-3	0.0406	0.0820	0.0964	0.0409	0.1944	0.4552	0.1063	0.2038
MT-4	0.1495	0.3512	0.0964	0.1545	0.0895	0.1860	0.1063	0.0912
MT-5	0.0557	0.1110	0.0964	0.0563	0.1799	0.4262	0.1063	0.1881
MT-6	0.0777	0.1699	0.0964	0.0789	0.1536	0.3674	0.1063	0.1596
MT-7	0.1523	0.3085	0.0964	0.1568	0.1209	0.2288	0.1063	0.1238
MT-8	0.0519	0.0957	0.0964	0.0524	0.1957	0.4416	0.1063	0.2049
MT-9	0.1150	0.1986	0.0964	0.1172	0.1599	0.3386	0.1063	0.1656
MT-10	0.1784	0.3590	0.0964	0.1846	0.1108	0.1783	0.1063	0.1129
MT-11	0.0655	0.1344	0.0964	0.0664	0.1797	0.4028	0.1063	0.1874

Table 9. *Positive and Negative Distances from Average Solution*

	Positive Distances from Average Solution d(AS)+				Negative Distances from Average Solution d(AS)-			
Material	dE(AS)+	dT(AS)+	σ(AS)+	d(AS)+	dE(AS)-	dT(AS)-	σ(AS)-	d(AS)-
MT-1	0.0126	0.0168	0.0930	0.0126	0.0388	0.0813	0.0404	0.0389
MT-2	0.0087	0.0127	0.0930	0.0087	0.0290	0.0538	0.0403	0.0291
MT-3	0.0404	0.0579	0.0930	0.0406	0.0439	0.0771	0.0403	0.0440
MT-4	0.0735	0.1400	0.0930	0.0745	0.0504	0.0705	0.0403	0.0505
MT-5	0.0447	0.0713	0.0930	0.0450	0.0364	0.0632	0.0403	0.0364
MT-6	0.0319	0.0541	0.0930	0.0321	0.0232	0.0327	0.0403	0.0231
MT-7	0.0696	0.1091	0.0930	0.0703	0.0635	0.1203	0.0403	0.0637
MT-8	0.0382	0.0550	0.0930	0.0384	0.0471	0.0830	0.0403	0.0472
MT-9	0.0807	0.1318	0.0930	0.0816	0.0314	0.0445	0.0403	0.0314
MT-10	0.1017	0.1549	0.0930	0.1031	0.0635	0.1184	0.0403	0.0638
MT-11	0.0155	0.0241	0.0930	0.0155	0.0436	0.0831	0.0403	0.0437

Table 10. *Comprehensive Distances and Final Ranking*

Material	*d(PIS)*	*d(NIS)*	*d(AS)+*	*d(AS)-*	*DC*	*Ranking*
MT-1	0.0622	0.1845	0.0126	0.0389	-0.0240	5
MT-2	0.0913	0.1493	0.0087	0.0291	-0.0094	8
MT-3	0.0409	0.2038	0.0406	0.0440	-0.0399	1
MT-4	0.1545	0.0912	0.0745	0.0505	0.0098	11
MT-5	0.0563	0.1881	0.0450	0.0365	-0.0351	3
MT-6	0.0789	0.1596	0.0321	0.0232	-0.0224	7
MT-7	0.1568	0.1238	0.0703	0.0638	0.0066	9
MT-8	0.0524	0.2049	0.0384	0.0473	-0.0359	2
MT-9	0.1172	0.1656	0.0816	0.0315	-0.0247	4
MT-10	0.1846	0.1129	0.1031	0.0638	0.0081	10
MT-11	0.0664	0.1874	0.0155	0.0437	-0.0232	6

Table 11. *Weighted Sum from PDA*

Material	*TS*	*EM*	*PR*	*VON*	*MD*	*RD*	*ES*	*CO*
MT-1	0.0000	0.0165	0.0052	0.0005	0.0071	0.0372	0.0371	0.0530
MT-2	0.0000	0.0000	0.0067	0.0005	0.0113	0.0154	0.0147	0.0000
MT-3	0.0330	0.0497	0.0000	0.0000	0.0000	0.0603	0.0602	0.0197
MT-4	0.0439	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000	0.0000
MT-5	0.0625	0.0283	0.0000	0.0000	0.0029	0.0493	0.0493	0.0000
MT-6	0.0151	0.0115	0.0057	0.0005	0.0000	0.0330	0.0331	0.0000
MT-7	0.0000	0.0000	0.0123	0.0008	0.0170	0.0000	0.0000	0.0697
MT-8	0.0057	0.0475	0.0000	0.0000	0.0000	0.0579	0.0575	0.0530
MT-9	0.0304	0.0272	0.0038	0.0005	0.0000	0.0451	0.0446	0.0000
MT-10	0.0000	0.0000	0.0124	0.0008	0.0222	0.0000	0.0000	0.0530
MT-11	0.0000	0.0165	0.0027	0.0001	0.0000	0.0379	0.0378	0.0697

3. Application of the EDAS Method

In this paper, we use EDAS approach to prioritize 11 alternative materials for robot prosthesis palm based on the weight of LOPCOW. This procedure consists of building a decision matrix, calculating the average criterion values, and measuring positive and negative distances based on Equations 26 to 30. Weighted sums are then calculated, divided by their maximum values, and a final appraisal score and the ranking of the alternatives is calculated according to Equation 31 to 35 as following applicable values has shown for efficient selection of 3D printing material for based on performance base criteria as shown in **Table 11 to 13**.

Table 12. *Weighted Sum from NDA*

Material	***TS***	***EM***	***PR***	***VON***	***MD***	***RD***	***ES***	***CO***
MT-1	0.0243	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MT-2	0.0417	0.0065	0.0000	0.0000	0.0000	0.0000	0.0000	0.0136
MT-3	0.0000	0.0000	0.0087	0.0005	0.0038	0.0000	0.0000	0.0000
MT-4	0.0000	0.0628	0.0261	0.0021	0.0000	0.0937	0.0924	0.0470
MT-5	0.0000	0.0000	0.0122	0.0008	0.0000	0.0000	0.0000	0.0303
MT-6	0.0000	0.0000	0.0000	0.0000	0.0030	0.0000	0.0000	0.0637
MT-7	0.0554	0.0589	0.0000	0.0000	0.0000	0.0981	0.0979	0.0000
MT-8	0.0000	0.0000	0.0017	0.0002	0.0222	0.0000	0.0000	0.0000
MT-9	0.0000	0.0000	0.0000	0.0000	0.0197	0.0000	0.0000	0.1637
MT-10	0.0459	0.0690	0.0000	0.0000	0.0000	0.1443	0.1440	0.0000
MT-11	0.0231	0.0000	0.0000	0.0000	0.0122	0.0000	0.0000	0.0000

Table 13. *Normalize Value of WSP, WSN and Final Ranking*

Material	WSP_i	WSN_i	$NWSP_i$	$NWSN_i$	FAS_i	***Rank***
MT-1	0.1566	0.0243	0.7027	0.9396	0.8212	5
MT-2	0.0486	0.0619	0.2179	0.8465	0.5322	8
MT-3	0.2229	0.0130	1.0000	0.9679	0.9839	1
MT-4	0.0443	0.3241	0.1987	0.1961	0.1974	11
MT-5	0.1924	0.0433	0.8631	0.8927	0.8779	3
MT-6	0.0988	0.0666	0.4431	0.8348	0.6389	6
MT-7	0.0998	0.3103	0.4476	0.2304	0.3390	9
MT-8	0.2216	0.0241	0.9942	0.9402	0.9672	2
MT-9	0.1516	0.1834	0.6801	0.5451	0.6126	7
MT-10	0.0883	0.4032	0.3964	0.0000	0.1982	10
MT-11	0.1647	0.0353	0.7390	0.9125	0.8257	4

The EDAS approach with the LOPCOW-based weighting criterion is successfully rank 11 materials for a robotic prosthetic palm. The highest score (0.9839) is given to Acrylic (MT-3) followed by PET (MT-8) and PA Type 6 (MT-5) with good overall value. Low-rank materials such as Nylon 101 (MT-4) and PP Copolymer (MT-10) are below average in deviation score as well as shown in **Table 13**. This method secures a well-balanced comparison, taking into account both positive and negative distances, for the precise and efficient material selection in 3D printing.

V. Assessment of Results

This section discusses a tri-phase strategy to examine the dependability of the results. In the first phase, the outcomes of the selected MCDM model are evaluated with those of the conventional methods, and the Copeland voting is utilized to rank the alternatives to get the overall ranking. The second stage is to estimate the Spearman rank correlation coefficient in order to quantify the level of agreement in the rankings obtained under the sel--ected method. Sensitivity analysis is the third stage used on RD criteria, to evaluate the stability and robustness of secondary ordinal rankings in different states.

1. Comparative Analysis of Various MCDM Methods and Consolidated Ranking

The assessment of 3D printing materials for prosthetic palm design involves comparing results from LOPCOW-COBRA and LOPCOW-EDAS methods with established MCDM techniques such as TOPSIS, WSM, WPM, WASPAS, PIV, and MOOSRA. The Copeland voting method [59] applies to achieve a detailed final ranking by integrating both victories and defeats of each alternative into the traditional Borda count. The WIN score for each alternative emerges by totaling its positions across all MCDM methods. The LOSS score emerges through deducting the positions of rival options from the WIN score. Each alternative's final performance score emerges through the subtraction of LOSS scores from WIN scores.

Through the integration of outcomes from eight distinct methods combined with Copeland aggregation, this research establishes a final priority list to determine the optimal material choice. Stakeholders in robotic prosthetic palm development can utilize the consolidated ranking presented in **Table 14** and **Fig. 3** as a decision-making tool that allows them to evaluate the eleven materials from most to least effective based on their exceptional characteristics.

Table 14. *Alternative's ranking.*

Material	*COBRA RANK*	*EDAS RANK*	*TOPSIS RANK*	*WSM RANK*	*WPM RANK*	*WASPAS RANK*	*PIV RANK*	*MOOSRA RANK*	*COPELAND RANK*
MT-1	5	5	3	5	5	5	4	3	5
MT-2	8	8	7	8	8	8	7	7	8
MT-3	1	1	1	2	2	2	1	1	1
MT-4	11	11	11	11	11	11	10	10	11
MT-5	3	3	5	3	4	4	3	4	3
MT-6	7	6	6	7	6	7	6	6	6
MT-7	9	9	9	9	9	9	9	9	9
MT-8	2	2	2	1	1	1	2	2	2
MT-9	4	7	8	6	7	6	8	8	7
MT-10	10	10	10	10	10	10	11	11	10
MT-11	6	4	4	4	3	3	5	5	4

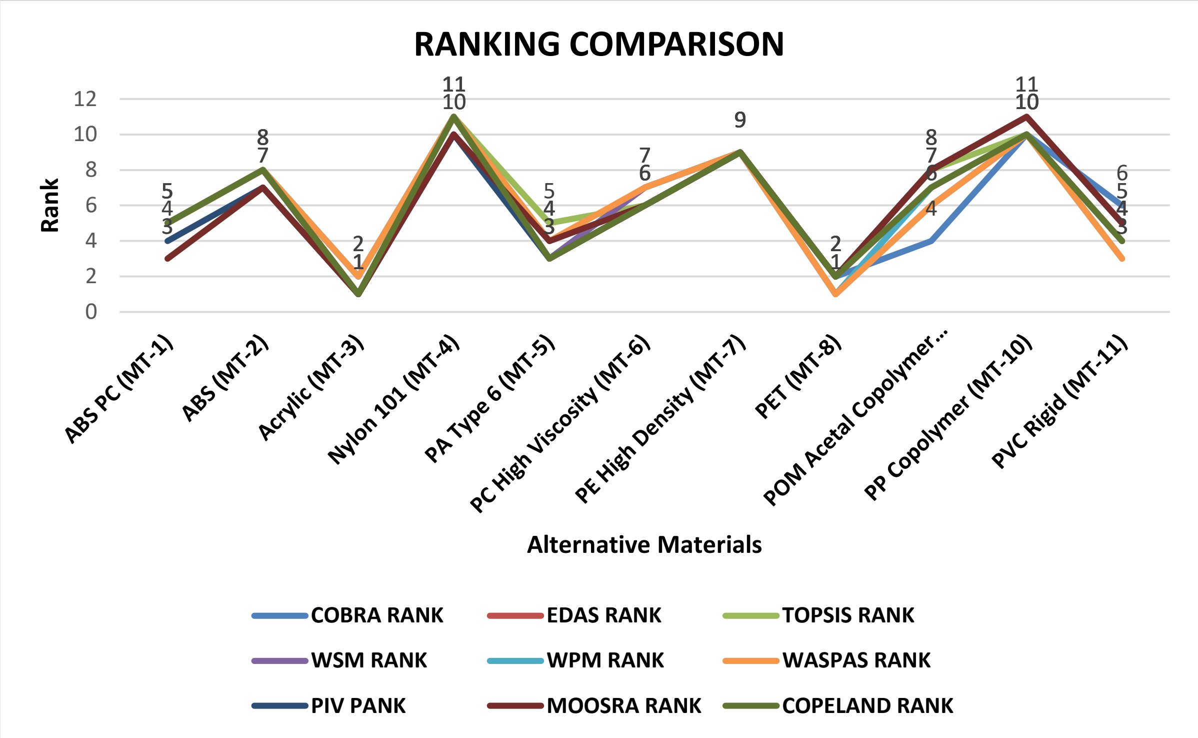


Figure 3. *Ranking Comparison of alternative materials with eight different MCDM method*

Among all materials, Acrylic (MT-3) is the best in all MCDM methods. It is ranked first in COBRA, EDAS, TOPSIS, PIV, and MOOSRA but placed second in WSM, WPM, and WASPAS. Due to high strength with a balanced elastic modulus at a moderate price and excellent strain displacement behaviour, Acrylic is preferred as the most suitable material for making prosthetic palms showing well-rounded characteristics matching highly weighted criteria that led to the first Copeland rank. The second-ranked material is PET (MT-8), which showed remarkable constancy since it was ranked first or second in all MCDM methods. Because of its low cost and strong mechanical performance as well as good strain behaviour, PET would be an excellent substitute for Acrylic. Its top-ranking performance in WSM, WPM, and WASPAS indicates that it performs well under purely additive as well as multiplicative evaluation frameworks.

PA Type 6 (MT-5) is achieved the third Copeland rank, exhibiting mid-to-high performance across all techniques. It presents a good balance of tensile strength, density, and strain-related properties, making it a suitable choice under cost-performance considerations. Close to fourth place was PVC Rigid (MT-11), which boasts excellent cost-effectiveness as well as structural integrity to support its use in non-flexible prosthetic components.

While none of the methods showed superiority, consistency is what keeps it among the leading performers. In fifth place was ABS PC (MT-1) with moderate to high performance for all criteria and methods. This material might have good printability coupled with moderate mechanical strength, thus making it an acceptable candidate under certain constraints. PC High Viscosity (MT-6) was ranked sixth without showing exceptional or significant underperformance in most criteria. This material would be particularly suitable for designs requiring flexibility or specific printing properties.

POM Acetal Copolymer showed the most variability in ranking, placed between 4th and 8th depending on the method, thus giving an overall rank of 7. Such variability may imply inconsistency in performance under highly critiqued criteria such as strain and displacement. ABS was consistently positioned at the eighth spot and PE High-Density at ninth, which indicates their performance consistency gets neither extreme nor too low- suggesting that these materials do not possess the required mechanical strength or flexibility to be used as prosthetic components. PP Copolymer was ranked tenth among the MCDM methods while Nylon 101 was placed eleventh. The two worst-performing materials had Copeland ranks of 10 and 11, respectively. All MCDM methods ranked them last or close to it, meaning they fail terribly in meeting desired mechanical as well as cost parameters. Nylon 101 has been rated eleventh in all processes; hence it would have very poor suitability for the concerned application.

This full multi-criteria study has identified Acryllic (MT-3) and PET (MT-8) as the two best materials for 3D printed prosthetic palm applications. These have the performance qualities we want at a less expensive cost, and they were stable in the ranking comparison figure 3 with almost all the MCDM ranking methods. These materials rate high based on heavy performance criteria weighting like strain, displacement and stress resistance. Other materials such as PA Type 6, PVC Rigid and ABS PC have at least some means of promise potentially based on design specifications. The least favorable candidates were Nylon 101 and PP Copolymer based on the majority of failing to reconcile over most of the performance criteria.

2. Spearman's rank correlation

This study evaluates the consistency of ranking outcomes across different methods using the Spearman rank correlation coefficient [60], calculated using Equation 36. This coefficient (SR_c) measures the correlation between rankings from various MCDM techniques, with values ranging from -1 to 1. Here, R_d represents the difference in ranks, and N_a is the number of alternatives. As shown in **Table 15**, the high Spearman coefficients (typically between 0.8 and 1.0) suggest strong agreement among the methods, confirming the reliability of the chosen ranking approach.

$$SR_c = 1 - \frac{6 \times \sum R_d^2}{N_a \times (N_a^2 - 1)} \qquad (36)$$

The Spearman correlation matrix reveals the degree of agreement between the eight applied MCDM techniques used to rank the 3D printing materials for prosthetic palm applications. Overall, the correlation coefficients range from 0.86 to 1.00, indicating a strong positive correlation across all methods. This consistency reflects the reliability of the techniques in evaluating alternatives and enhances confidence in the final decision outcomes. Among the combinations, EDAS and WSM display an exceptionally high correlation of 0.9818, closely followed by WPM and WASPAS with 0.9909, and PIV and MOOSRA with 0.9909 as well. These values suggest that these pairs of methods generate nearly identical rankings, highlighting their compatibility and similar evaluation logic.

Interestingly, TOPSIS and COBRA present the lowest correlation at 0.8636, though still within a high agreement range. This indicates that while COBRA and TOPSIS are somewhat aligned, their assessment criteria or algorithmic focus may differ more significantly compared to other method pairs. WSM, WPM, and WASPAS are among the most consistently aligned methods, each correlating highly with the others and with EDAS, reflecting their shared foundation in weighted-sum or product-based logic. Meanwhile, MOOSRA also shows

Table 15. *Spearman correlation scores between MCDM Techniques*

	COBRA	***EDAS***	***TOPSIS***	***WSM***	***WPM***	***WASPAS***	***PIV***	***MOOSRA***
COBRA	1.0000	0.9364	0.8636	0.9545	0.9000	0.9273	0.9000	0.8818
EDAS	0.9364	1.0000	0.9545	0.9818	0.9818	0.9727	0.9727	0.9545
TOPSIS	0.8636	0.9545	1.0000	0.9273	0.9545	0.9364	0.9636	0.9818
WSM	0.9545	0.9818	0.9273	1.0000	0.9818	0.9909	0.9455	0.9273
WPM	0.9000	0.9818	0.9545	0.9818	1.0000	0.9909	0.9455	0.9364
WASPAS	0.9273	0.9727	0.9364	0.9909	0.9909	1.0000	0.9273	0.9182
PIV	0.9000	0.9727	0.9636	0.9455	0.9455	0.9273	1.0000	0.9909
MOOSRA	0.8818	0.9545	0.9818	0.9273	0.9364	0.9182	0.9909	1.0000

strong correlation values with all others, particularly with TOPSIS and PIV, emphasizing its robustness and agreement with the broader evaluation framework. So, the Spearman correlation analysis validates the coherence and robustness of the employed MCDM techniques. The strong inter-method correlations reinforce the credibility of the final material rankings, particularly those aggregated through the Copeland method. This suggests that decision-makers can confidently rely on the outcomes of this comparative analysis when selecting materials for prosthetic palm design.

3. Sensitivity Analysis on the presented study

This section of the paper examines the reliability and the stability of the two MCDM techniques which have been applied in the study. In real-world applications, the input of the stakeholders is often based on their own insights and preferences, which are usually shaped through their experiences and their expertise. Though these inputs are precious, sometimes they can create biases which may lead to uncertainty and thus be one of the reasons that the decision outcomes would be affected. The first step in the sensitivity analysis is to modify the weight of the criteria in the decision-making process systematically so that it is possible to measure how different criteria alterations impact the final ranks. For instance, the pre-study has eight aspects that are used to rank the candidate materials for prosthetic palm design. The first step is to find the most influential criteria (MIC) by using a criteria weighting method.

Ciphering the weight of this criterion is the next procedure that provides an understanding of how the rankings are influenced by the MIC weight. Here, one can know the degree of ranking consistency which would depend exclusively on the MIC weight and thus know the weaknesses and strengths of the MCDM model vis-à-vis the changes of the decision-making context.

The process of sensitivity analysis by criterion weight variation is explained through the following.

Step 1: Estimation of Elastic Weight Coefficient (E_{WC})

Elastic Weight Coefficient serves as an indicator of how changes in MIC's weight impact the balance among all other criteria. It reflects the proportional adjustment required for the remaining weights when the MIC's weight is modified. For the MIC itself, this coefficient is always set to 1, indicating full impact. For the other parameters, Equation 37 is used to compute their respective coefficients.

$$E_{WC} = \frac{O_w}{1 - O_{wmic}} \tag{37}$$

Where, O_w is the original weight of the criterion being adjusted, $O_{wmic}$is the weight of the most influential criteria. This calculation ensures that changes in one parameter are properly compensated by adjustments in others, maintaining the overall balance of the weight distribution. The resulting E_{WC} values are listed in **Table 16**.

Step 2: Determination of Permissible Weight Variation (Δx)

This step involves in calculating the Δx factor, which represents the extent of weight variation applied to the criteria set based on the corresponding elastic weight coefficients. To maintain validity, the adjusted weight of the most influential criteria must not exceed certain bounds; otherwise, it may cause some weights to become negative, violating the condition of weight non-negativity. A positive Δx implies an increase in relative influence, while a negative Δx implies a reduction. Equation (38) is used to define the permissible range of Δx, and the resulting limits are listed in **Table 16**.

$$-O_{wmic} \leq \Delta X \leq MIN\left(\frac{O_w}{O_{wmic}}\right) \tag{38}$$

Step 3: Recalculation of Updated Weights based on Δx

In this step, new weights for the MIC and the remaining criteria are determined using Equation 39. The updated weight of the MIC (W_{nu}) is calculated by adding the product of the elastic weight

Table 16. *E_{WC} with varying weights*

Criteria	*Calculated Weight*	E_{WC}	*ΔX*
W-6 (RD)	0.1417	1	-
W-1 (TS)	0.0938	0.1092	0.8583
W-2 (EM)	0.1191	0.1387	0.8583
W-3 (PR)	0.1307	0.1523	0.8583
W-4 (VON)	0.1400	0.1630	0.8583
W-5 (MD)	0.0967	0.1126	0.8583
W-7 (ES)	0.1416	0.1649	0.8583
W-8 (CO)	0.1364	0.1589	0.8583

coefficient and Δx to the original MIC weight. Conversely, for the other criteria, their new weights (W_{no}) are obtained by subtracting this product from their original values (O_w). This adjustment ensures that the total of all new weights remains normalized (i.e., their sum equals 1), maintaining proportionality. The corresponding values are presented in **Table 17**.

$$W_{nu} = O_{wmic} + (E_{wc} \times \Delta X)$$
$$W_{no} = O_w - (E_{wc} \times \Delta X) \quad (39)$$

Any alteration in the weights of the criteria (derived through the ranking technique) can significantly affect the final order of the available alternatives in certain cases. To assess the consistency and resilience of the decision-making model, a sensitivity analysis was conducted to identify if such variations might occur. For this purpose, the allowable range of weight variation (Δx) for parameter "W6" was calculated, ranging from -0.1417 to 0.8583. After establishing these boundaries, 22 different weight scenarios were generated using Equation 39, as presented in **Table 17**. This table also indicates that when Δx equals 0, the weights across all criteria match their initial values, confirming the consistency of the original setup.

For example, the 3rd alternative is constantly the top performer (Rank 1) under all scenarios, thus, giving evidence of the unprecedentedly strong stability and performance of the system independent of the variation in the criteria weights.

Correspondingly, the 5th alternative is solid at Rank 3, and the 8th and 9th alternatives continue to secure Ranks 2 and 4, respectively as shown in **Fig. 4**. This is the evidence of the fact that these materials are indeed very robust and can be recommended with great confidence even under changed decision conditions. Contrarily, materials like the 4th and the 11th are not that much affected. At first, the 4th alternative moves up from Rank 11 in scenarios 1 to 5 (C1–C5) to Rank 9 in scenarios 11 to 22 (C11–C22), and the 11th alternative changes from Rank 6 to Rank 5 in the middle positions. These changes make it clear that their orders are tied to the specific criteria that are accentuated by the weight. Further, the 2nd (always Rank 8), 6th (always Rank 7), and 7th (always Rank 9) alternatives, though not identical, have similar stable performances in the mid-tier, maintaining their positions neither extraordinarily well nor significantly declining from the best. As for the 10th alternative, the drop from Rank 10 to 11 after the fifth scenario shows that the level of sensitivity is small. Generally speaking, the rankings distribution emphasizes the credibility of the decision-making framework—one that can track the meaningful alterations as weights change, while simultaneously upholding the stability of the best options under different evaluation scenarios.

Table 17. *New Criteria Weight (W_{nu} and W_{no})*

Case	*del X*	*W-1*	*W-2*	*W-3*	*W-4*	*W-5*	*W-6*	*W-7*	*W-8*	*Total*
C1	-0.142	0.109	0.139	0.152	0.163	0.113	0.000	0.165	0.159	1.000
C2	-0.100	0.105	0.133	0.146	0.156	0.108	0.042	0.158	0.152	1.000
C3	-0.050	0.099	0.126	0.138	0.148	0.102	0.092	0.150	0.144	1.000
C4	0.000	0.094	0.119	0.131	0.140	0.097	0.142	0.142	0.136	1.000
C5	0.050	0.088	0.112	0.123	0.132	0.091	0.192	0.133	0.128	1.000
C6	0.100	0.083	0.105	0.116	0.124	0.085	0.242	0.125	0.121	1.000
C7	0.150	0.077	0.098	0.108	0.116	0.080	0.292	0.117	0.113	1.000
C8	0.200	0.072	0.091	0.100	0.107	0.074	0.342	0.109	0.105	1.000
C9	0.250	0.066	0.084	0.093	0.099	0.069	0.392	0.100	0.097	1.000
C10	0.300	0.061	0.077	0.085	0.091	0.063	0.442	0.092	0.089	1.000
C11	0.350	0.056	0.071	0.077	0.083	0.057	0.492	0.084	0.081	1.000
C12	0.400	0.050	0.064	0.070	0.075	0.052	0.542	0.076	0.073	1.000
C13	0.450	0.045	0.057	0.062	0.067	0.046	0.592	0.067	0.065	1.000
C14	0.500	0.039	0.050	0.055	0.058	0.040	0.642	0.059	0.057	1.000
C15	0.550	0.034	0.043	0.047	0.050	0.035	0.692	0.051	0.049	1.000
C16	0.600	0.028	0.036	0.039	0.042	0.029	0.742	0.043	0.041	1.000
C17	0.650	0.023	0.029	0.032	0.034	0.023	0.792	0.034	0.033	1.000
C18	0.700	0.017	0.022	0.024	0.026	0.018	0.842	0.026	0.025	1.000
C19	0.750	0.012	0.015	0.016	0.018	0.012	0.892	0.018	0.017	1.000
C20	0.800	0.006	0.008	0.009	0.010	0.007	0.942	0.010	0.009	1.000
C21	0.850	0.001	0.001	0.001	0.001	0.001	0.992	0.001	0.001	1.000
C22	0.858	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000

Fig. 5 shows the rankings of 11 alternatives under 22 different weight scenarios (C1–C22). Each alternative is shown how it performs in different decision contexts using LOPCOW-EDAS. The most notable finding is the 3rd alternative which is always Rank 1 across all scenarios, it's very robust and perform well regardless of changes in criteria weight.

The 5th alternative is also consistent at Rank 3, the 8th alternative at Rank 2, and the 6th and 7th at 6 and 9 respectively. The 4th alternative is sensitive to weight changes, its Rank 11 from C1 to C4, then Rank 10 from C5 to C18 and finally Rank 9 from C19 onwards. Its performance gets better as the weight scheme evolves.

The 9th alternative is also sensitive, it's Rank 8, then Rank 7 from C2 to C5, Rank 6 from C6 to C12 and finally Rank 5 from C13 to C22. It's a big upward trend. The 11th alternative is Rank 4 to 5 in the last few scenarios, its moderate sensitive. The 10th alternative is slightly down, it's Rank 10 from C1 to C4 and then consistently Rank 11 afterwards.

Overall the **Fig. 5** shows a ranking framework that shows both robust and sensitive alternatives. The 3rd, 5th and 8th alternatives are not affected by weight changes while the 4th, 9th and 11th alternatives show the model can detect performance shifts due to weight changes, thus the sensitivity analysis is working.

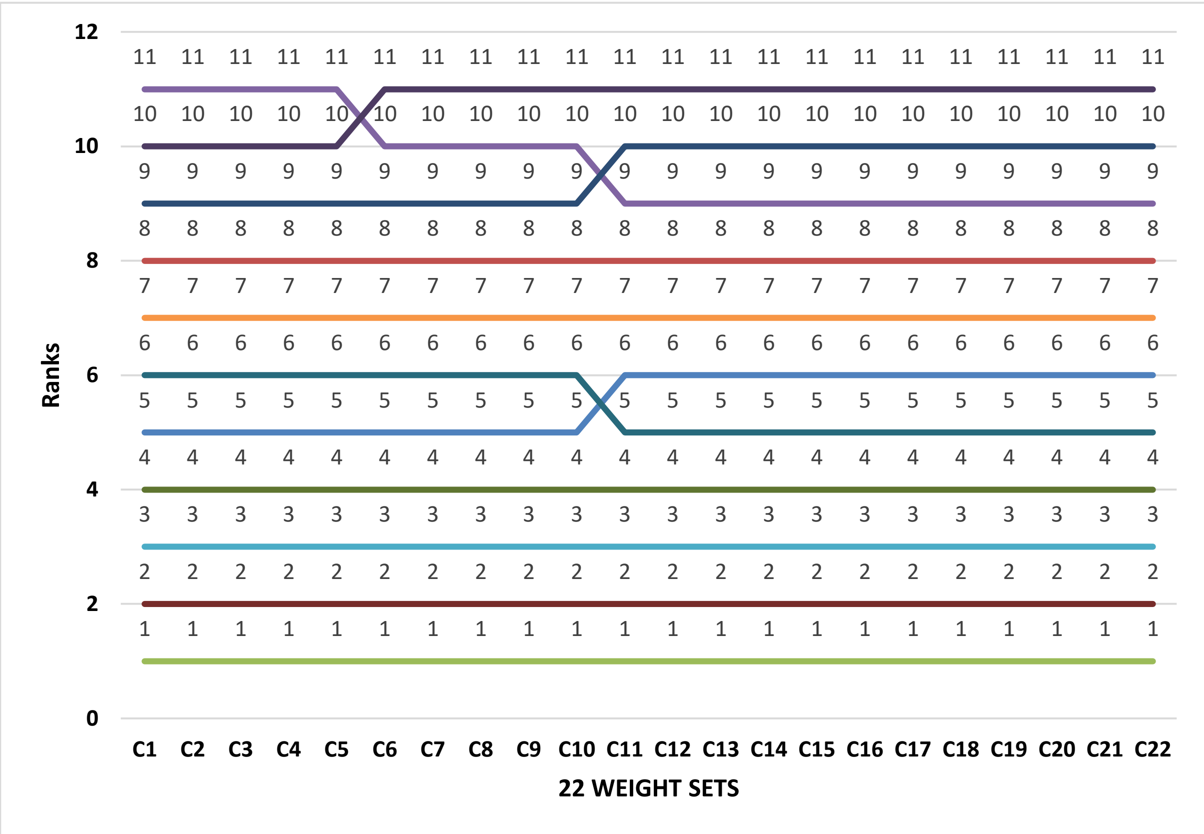


Figure 4. *LOPCOW-COBRA Sensitivity Analysis*

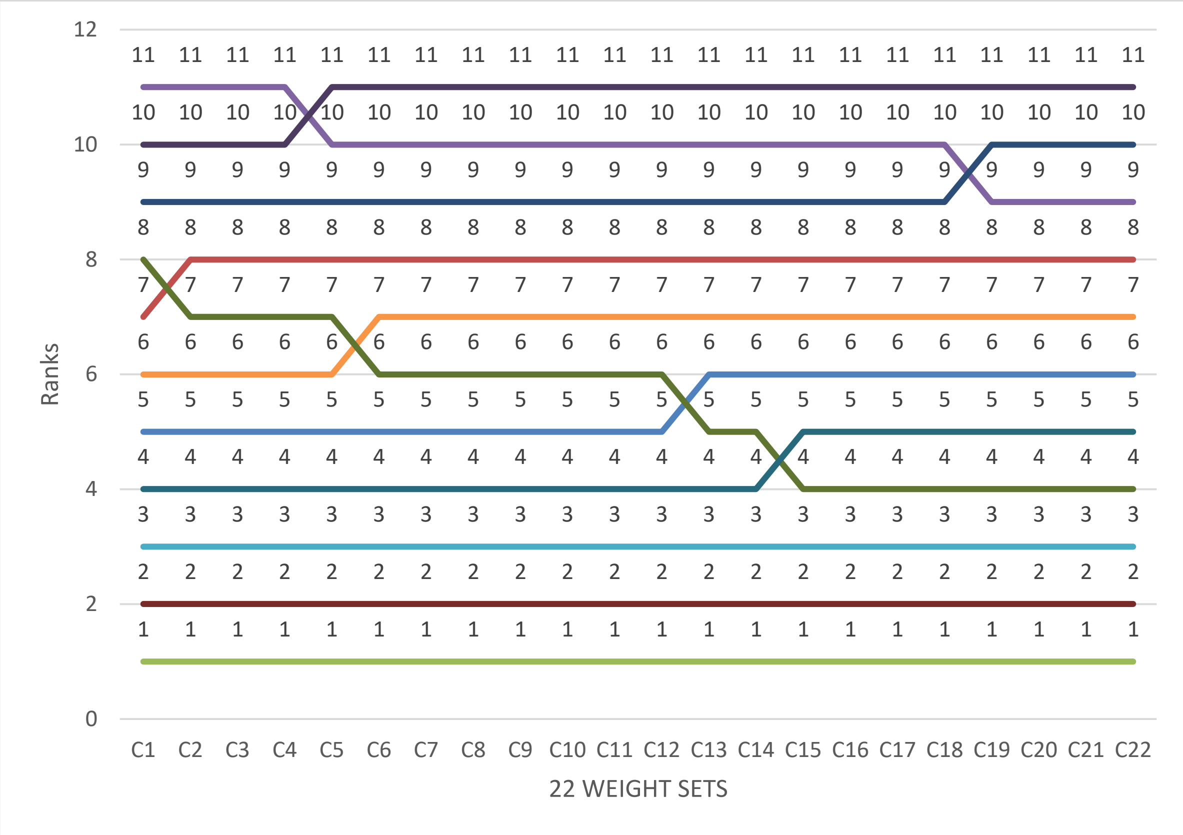


Figure 5. *LOPCOW-EDAS Sensitivity Analysis*

VI. Conclusion

This paper presents a robust and integrated decision making framework combining LOPCOW, COBRA and EDAS methods to select materials for the design of a robotic prosthetic palm. The framework provides a systematic way to evaluate and rank multiple 3D printing material alternatives based on multiple performance criteria.

i. Through LOPCOW methodology eight essential criteria weights were determined which highlight Resultant Displacement (0.1417), Equivalent Strain (0.1416), and Max von Mises Stress (0.1400) as key factors for assessing 3D printing materials in biomechanical uses.

ii. The application of both COBRA and EDAS methods resulted in the ranking of materials. The investigation revealed consistent and insightful results which demonstrated dual-method validation as a valuable approach for obtaining reliable material rankings.

iii. Through the application of Copeland voting methodology to consolidate outcomes, Acrylic (MT-3) attained the position of top-performing material with PET (MT-8) and PA Type 6 (MT-5) following in rank. The proposed evaluation system demonstrates significant strength through reinforced robustness.

iv. Nylon 101 (MT-4) and PP Copolymer (MT-10) emerged at the bottom of the ranking list indicating their unsuitability for prosthetic palm applications because they perform poorly against essential criteria.

v. Materials such as Acrylic represent top-tier choices because they deliver exceptional mechanical strength while maintaining flexibility and cost-effectiveness, which makes them perfect for creating patient-specific prosthetic palms.

vi. Displacement and strain criteria receive substantial weight assignments because they powerfully affect prosthetic performance to guarantee user safety along with durability and comfort.

vii. The Spearman correlation coefficient of 0. The value 9364 in LOPCOW-COBRA and LOPCOW-EDAS rankings demonstrates exceptional methodological agreement. The robust concordance serves as evidence for the integrated MCDM framework's dependability while simultaneously boosting trust in the material selection results.

viii. The LOPCOW–COBRA–EDAS framework demonstrates adaptability for diverse medical device applications and general engineering problems requiring efficient material selection.

1. Practical Implementation

LOPCOW, COBRA and EDAS together provide a robust decision making framework for selecting the best 3D printing materials for robotic prosthetic palm design. This approach improves product performance, reduces manufacturing cost and user comfort. The top ranked materials like Acrylic and PET offer a practical balance of strength, flexibility and cost, making the prosthetic more functional, customizable and accessible for real world rehabilitation and clinical applications

2. Limitation

One limitation of this study is the use of simulated material properties which may not capture the complexity of real world prosthetic applications. The selected criteria though comprehensive may miss out factors like long term durability or biocompatibility. Also the MCDM methods assume stable and consistent parameter weightings which may vary with user specific needs or evolving technologies and may affect the generalizability of the material selection results.

3. Future Scope

This work could be extended in future to evaluate durability, comfort and user acceptance under real use conditions. If more decision variable, such as environmental influence, recyclability, and bio-compatibility are included, the selection of the material becomes more promising and robust.

Acknowledgement

The authors are thankful to supports and facilities from Indira Gandhi Institute of Technology (IGIT), Sarang, and without it, this work would have not been possible. We are also grateful to Biju Patnaik University of Technology (BPUT) for their kind co-operation and support throughout the study.

AUTHOR CONTRIBUTIONS

I. Dhar: Conceptualization, Theoretical analysis, and Writing.

B. B. Choudhury: Conceptualization, Review and Supervising.

B. Sahoo: Conceptualization, Review and Supervising.

S. K. Sahoo: Conceptualization, SolidWork modelling, Writing, Review and editing.

D. Pamucar: Conceptualization, Review and editing.

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Disclosure Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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