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RESEARCH ARTICLE

Comparative Evaluation of Advanced Robotics in Engineering Using the COPRAS Method

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ABSTRACT: This research paper presents a comparative analysis of five advanced robotics systems RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7, and NanoDrive R3 in the field of engineering using the COPRAS (COmplex PRoportional ASsessment) method. The study evaluates these alternatives based on four benefit and four non-benefit parameters: load capacity, energy efficiency, cost, and maintenance frequency. The COPRAS method is employed to rank these systems based on their overall performance, considering both quantitative and qualitative factors. The analysis begins with the creation of a normalized decision matrix to compare the robots based on the given parameters. Weightings are assigned equally to each criterion, ensuring an unbiased comparison. The results show that AutoBot v7 ranks first with a QI (Quality Index) of 0.208 and a UI (Utility Index) of 100%, demonstrating optimal performance across all criteria, especially in cost-effectiveness and maintenance frequency. MechFlex Pro follows closely in second place with a QI of 0.207 and UI of 100%, excelling in load capacity but slightly behind in cost efficiency. NanoDrive R3 ranks third, boasting the highest energy efficiency but offset by its higher cost, resulting in a UI of 98%. Conversely, RoboX2000 and TechArm Max rank fourth and fifth, respectively, due to lower performance in specific criteria like cost and maintenance frequency. These findings are further supported by visual representations of the normalized data and rankings, highlighting the comparative strengths and weaknesses of each robotic system. Overall, this research provides valuable insights for decision-makers in the engineering field by identifying the most suitable robotic solutions based on multi-criteria evaluation. The COPRAS method proves to be a robust tool for comparing advanced technologies, ensuring optimal selection based on diverse performance indicators.

Keywords: Advanced Robotics, COPRAS Method, Engineering Applications, Multi-Criteria Decision Making (MCDM)

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1. INTRODUCTION

In recent decades, robotics has emerged as a cornerstone of engineering innovation, reshaping industries by enhancing precision, productivity, and safety [1]. The integration of robotics into engineering disciplines has opened up transformative opportunities, allowing engineers to address complex challenges that were once deemed insurmountable [2]. Robotics, particularly advanced robotics, is at the heart of industrial automation, aerospace engineering, healthcare, construction, and even environmental sustainability [3]. This confluence of robotics and engineering forms the foundation of the rapidly evolving field of Advanced Robotics in Engineering, which strives to develop intelligent, efficient, and adaptable robotic systems capable of performing intricate tasks across diverse sectors [4, 5]. Advanced robotics involves the design, creation, and deployment of robotic systems that can perform tasks autonomously or semi-autonomously, often in unstructured or dynamic environments. These robots typically employ sophisticated sensing technologies, artificial intelligence (AI), and machine learning algorithms to interact with their surroundings, make real-time decisions, and improve over time through self-learning [6, 7]. The overarching goal of advanced robotics in engineering is to develop systems that enhance human capabilities, reduce the risk of human error, and optimize efficiency in engineering processes [8]. To achieve this, researchers and engineers are continuously pushing the boundaries of what robots can do, from creating

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robots that can manipulate microscopic objects in biomedical applications to those that can construct large-scale infrastructure projects [9]. One of the primary areas where advanced robotics has made significant strides is industrial automation. In manufacturing, robots are increasingly used for precision-driven tasks such as assembly, welding, painting, and packaging. These tasks require a high degree of accuracy, consistency, and speed, making robots ideal for the job. Advanced robotics, in particular, enables the automation of processes that were previously too complex or delicate for traditional machinery [10, 11]. Robots equipped with AI-powered vision systems can identify objects, assess their positions, and manipulate them with incredible precision, all while adapting to changes in the production environment. This adaptability is particularly crucial in industries such as electronics and automotive manufacturing, where products are becoming increasingly complex, and the need for flexibility in production lines is growing [12]. The integration of robotics into construction engineering is another exciting development. Historically, construction has been a labor-intensive industry with many inherent risks.

However, with the advent of advanced robotics, this sector is undergoing a digital transformation. Robots are now being developed to perform tasks such as bricklaying, concrete pouring, and even autonomous surveying. These robots can work alongside human laborers to increase efficiency, reduce costs, and minimize the risks associated with hazardous working conditions [13, 14]. In addition to physical construction tasks, robots are being used in the design and planning phases of engineering projects. For instance, robotic systems equipped with AI and machine learning algorithms can simulate complex architectural designs, helping engineers identify potential flaws and optimize structures before they are built [15]. Aerospace engineering, one of the most technologically advanced fields, also benefits from robotic innovations. Robots have long been utilized in the aerospace industry for assembling aircraft and spacecraft components with high precision, but the development of autonomous drones and robotic rovers has opened up new possibilities for exploration and maintenance tasks [16, 17]. Autonomous drones equipped with sophisticated sensors are used for inspecting aircraft, bridges, and even space stations, reducing the need for risky human interventions. In planetary exploration, robotic systems such as NASA's Mars rovers exemplify the synergy between robotics and engineering. These advanced robots can autonomously navigate and analyze extraterrestrial environments, collect data, and perform experiments that were once only achievable with manned missions [18]. The use of robotics in aerospace engineering not only enhances precision but also reduces costs and increases the frequency of missions, advancing scientific knowledge. Healthcare is another domain where advanced robotics is revolutionizing engineering [19]. Robotic systems are increasingly being deployed in medical settings, both for surgeries and patient care. Robotic-assisted surgeries, for instance, allow surgeons to perform delicate procedures with greater accuracy and control, leading to faster recovery times and reduced risks for patients.

In addition to surgical applications, robots are used in rehabilitation engineering to assist patients with physical therapy and mobility training. These robots can adapt to the needs of individual patients, providing personalized care and feedback, which enhances the effectiveness of rehabilitation programs [20]. Furthermore, robotic systems are being developed for use in diagnostic applications, where they can analyze medical images, detect anomalies, and assist in early disease detection. The future of healthcare engineering will likely see more integration of robotics, as advancements in AI and machine learning enable robots to take on more complex tasks, such as diagnosing diseases and even administering treatments [21]. The field of environmental engineering is also witnessing the rise of advanced robotics. Environmental engineers are increasingly utilizing robots to monitor and manage natural resources, assess environmental damage, and assist in disaster response efforts. For instance, underwater robots are used to explore and map the ocean floor, monitor marine life, and detect changes in water quality. In disaster-stricken areas, robots can be deployed to assess damage, search for survivors, and even assist in rebuilding efforts [22]. The use of robots in environmental engineering not only reduces the risks to human workers but also provides more accurate and timely data for decision-making processes.

As environmental concerns such as climate change and resource depletion become more pressing, the role of robotics in monitoring and mitigating environmental impacts will likely expand. While the benefits of advanced robotics in engineering are evident, there are also challenges that need to be addressed [23]. One of the most significant challenges is the cost of developing and implementing robotic systems. Advanced robots are expensive to design, build, and maintain, which can be a barrier for smaller engineering firms or industries with tight budgets [24]. However, as technology continues to evolve, the costs are expected to decrease, making robotics more accessible to a broader range of industries. Another challenge is the need for skilled labor to operate and maintain these advanced systems. As robots become more integrated into engineering processes, there will be an increasing demand for engineers and technicians with expertise in robotics, AI, and data analytics. This necessitates a shift in educational and training programs to prepare the future workforce for a robotics-driven world [25-28]. Advanced robotics in engineering is an exciting and rapidly growing field that holds immense potential to transform industries and improve the quality of human life [29, 30]. From industrial automation and construction to aerospace, healthcare, and environmental engineering, robotics is playing an increasingly central role in addressing some of the most complex challenges faced by engineers today [31-33]. The continued development of robotics technologies, coupled with advancements in AI and machine learning, will likely lead to even more innovative applications in the future. While there are challenges to overcome, such as cost and the need for skilled labor, the benefits of integrating advanced robotics into engineering processes far outweigh the drawbacks [34, 35]. As research and development in this field continue to progress, we can expect to see a future where robotics and engineering are inextricably linked, driving innovation and shaping the world of tomorrow.

In this article, we explore the application of the COPRAS method for evaluating five different robotic systems in engineering, based on eight key evaluation parameters. The evaluation of robotic systems involves numerous factors, both technical and economic, that influence the decision-making process. To provide a structured assessment, we considered five advanced robotic systems: RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7, and NanoDrive R3. These alternatives represent different robotic solutions that are commonly employed in engineering applications. Each robotic system was evaluated based on four benefit parameters and four non-benefit parameters. The benefit parameters included Precision, Speed, Load Capacity, and Energy Efficiency. These parameters reflect the performance capabilities of the robotic systems, with higher values indicating superior performance. On the other hand, the non-benefit parameters—Cost, Maintenance Frequency, Power Consumption, and Space Requirement—reflect aspects where lower values are preferable, as they relate to operational costs and efficiency.

2. PROPOSED WORK

In today's rapidly evolving technological landscape, advanced robotics has become a cornerstone in engineering, offering numerous advantages in precision, efficiency, and automation. The adoption of robotics systems in various engineering sectors has enabled the improvement of productivity and quality in complex processes. However, selecting the most suitable robotic system for engineering applications requires a systematic approach that considers multiple evaluation criteria. One of the most effective methods for multi-criteria decision-making (MCDM) in this context is the COPRAS (COmplex PRoportional ASsessment) method. COPRAS is a well-known decision-making tool that allows for the evaluation of alternatives based on multiple benefit and non-benefit parameters, providing a comprehensive analysis of performance and efficiency.

2.1. Defining the Benefit and Non-Benefit Parameters

In the context of robotics in engineering, benefit parameters are key performance indicators that influence the effectiveness of a robotic system. For instance, Precision refers to the robot's ability to perform tasks with minimal error, which is crucial for high-accuracy operations such as assembly, welding, or material handling. In the dataset, RoboX2000 and NanoDrive R3 have the highest precision, both offering a precision level of 0.01 mm, which is vital for tasks requiring fine-tuned accuracy. Speed, another benefit parameter, measures how fast the robotic system can operate. NanoDrive R3 exhibits the highest speed at 2.0 m/s, making it suitable for operations where quick processing times are essential. Load Capacity is another critical benefit parameter, especially in applications where heavy objects need to be lifted or moved. The MechFlex Pro, with a load capacity of 200 kg, outperforms the other systems in this aspect, making it ideal for heavy-duty operations. Lastly, Energy Efficiency is a measure of how effectively the robotic system utilizes energy, an increasingly important factor in industries aiming to reduce their environmental footprint. The NanoDrive R3, with an energy efficiency of 92%, leads in this category, providing significant operational savings over time. On the flip side, non-benefit parameters represent operational challenges or costs associated with using a robotic system. Cost is a primary concern for many organizations, and in our dataset, the AutoBot v7 offers the most cost-effective solution at USD 65,000, making it attractive for budget-conscious engineering firms. Maintenance Frequency refers to how often the robotic system requires maintenance, with lower values indicating fewer interruptions to workflow. NanoDrive R3, with a maintenance frequency of 3.5 times per year, stands out as the most reliable system in terms of reduced maintenance needs. Power Consumption is another critical non-benefit parameter, where TechArm Max consumes the least energy at 7.5 kW, contributing to lower operational costs. Finally, Space Requirement reflects the amount of physical space needed for the robotic system, which can be a limiting factor in cramped industrial environments. The NanoDrive R3 requires the least space at 12 m², making it suitable for compact workspaces.

2.2. Application of the COPRAS Method

The COPRAS method provides a structured approach for evaluating alternatives based on both benefit and non-benefit parameters. The method starts by normalizing the decision matrix, which involves transforming the raw data into dimensionless values, allowing for comparisons between different units of measurement. For benefit parameters, the normalized value is calculated by dividing each parameter value by the maximum value in its category. For non-benefit parameters, the normalization is done by dividing the minimum parameter value by each individual value. This ensures that the evaluation remains consistent, with higher values representing better performance for both benefit and non-benefit parameters after normalization. Once the decision matrix has been normalized, the next step involves calculating the weighted significance of each alternative. In many practical applications, decision-makers assign different weights to parameters based on their relative importance. For instance, in a high-precision engineering application, the weight of the Precision parameter might be higher than that of Speed or Cost. In this hypothetical scenario, we assume equal weights for all parameters for simplicity. The weighted normalized values are then calculated by multiplying the normalized values by their corresponding weights. The COPRAS method proceeds by calculating the sums of the weighted normalized values for benefit parameters (**S+i**) and non-benefit parameters (S-i) for each alternative. These sums represent the overall performance of the alternatives in terms of their benefit and non-benefit characteristics. The total relative importance of each alternative is then calculated using the formula:

$$Q_i = S_i^+ - \frac{S_i^+}{\sum S_i^-} \times \sum S_i^+ \quad (1)$$

The relative importance of each alternative, Si+ is the sum of the weighted benefit parameters, and Si− is the sum of the weighted non-benefit parameters. Using the COPRAS method, each robotic system is ranked based on its relative importance score (Q_i), which reflects its overall suitability for engineering applications. The robotic system with the highest QiQ_iQi value is considered the best alternative. In our analysis, NanoDrive R3 emerges as the most favorable system, primarily due to its high scores in benefit parameters such as Precision, Speed, and Energy Efficiency, combined with its low values in non-benefit parameters like Maintenance Frequency and Space Requirement. MechFlex Pro also performs well, particularly in Load Capacity and Maintenance Frequency, making it a strong candidate for heavy-duty applications where reliability and operational uptime are critical. On the other hand, while AutoBot v7 offers the lowest cost, its performance in other benefit parameters such as Precision and Load Capacity is comparatively lower, making it less suitable for high-precision tasks. RoboX2000 and TechArm Max offer balanced performance across several categories, but they are outperformed by NanoDrive R3 in terms of overall efficiency and versatility. The COPRAS method offers a robust and systematic approach to evaluating multiple robotic systems in engineering applications, taking into account both benefit and non-benefit parameters. By normalizing the decision matrix and calculating the relative importance of each alternative, decision-makers can objectively rank the alternatives based on their performance across multiple criteria. In our analysis, NanoDrive R3 emerges as the best option for advanced robotics in engineering, offering a balance of high precision, speed, energy efficiency, and low operational costs. However, the final decision depends on the specific requirements of the engineering application, and decision-makers may choose to adjust the weights of the parameters based on their unique needs. As the field of robotics continues to evolve, the integration of advanced decision-making methods like COPRAS will become increasingly important in selecting the most efficient and effective robotic systems for engineering tasks. The ability to evaluate alternatives based on multiple criteria ensures that organizations can optimize their operations, reduce costs, and enhance the quality of their products and services.

3. RESULTS AND DISCUSSION

Table 1 provides a comparative evaluation of five advanced robotic systems RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7, and NanoDrive R3—based on key performance indicators using the COPRAS (COmplex PRoportional ASsessment) method. The parameters compared include Load Capacity (kg), Energy Efficiency (%), Cost (USD), and Maintenance Frequency (times/year). In terms of Load Capacity, MechFlex Pro stands out with the highest capacity at 200 kg, making it the best choice for heavy-duty applications. TechArm Max follows closely with 180 kg, while RoboX2000 offers a moderate 150 kg load capacity. NanoDrive R3, despite being more compact, can handle 160 kg, reflecting its balance between efficiency and performance. When considering Energy Efficiency, NanoDrive R3 excels with an impressive 92%, making it the most energy-efficient, followed by TechArm Max at 90% and AutoBot v7 at 88%. RoboX2000 and MechFlex Pro lag slightly behind at 85% and 80%, respectively. In terms of Cost, AutoBot v7 is the most affordable at USD 65,000, while NanoDrive R3 is the most expensive at USD 85,000. Maintenance Frequency is lowest for NanoDrive R3 at 3.5 times/year, indicating higher reliability, while TechArm Max requires the most maintenance at 6 times/year. Overall, NanoDrive R3 offers the best balance of energy efficiency, moderate load capacity, and low maintenance frequency, while MechFlex Pro is ideal for high load capacity applications.

Figure 1 depicts a comparative evaluation of five advanced robotic systems RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7, and NanoDrive R3 based on key parameters using the COPRAS (COmplex PRoportional ASsessment) method. The parameters visualized in the bar graph are Load Capacity (kg), Cost (USD), Energy Efficiency (%), and Maintenance Frequency (times/year).

Table 1. Advanced Robotics in Engineering.

Advanced Robotics in Engineering				
	Load Capacity (kg)	**Energy Efficiency (%)**	**Cost (USD)**	**Maintenance Frequency (times/year)**
RoboX2000	150	85	75,000	5
MechFlex Pro	200	80	80,000	4
TechArm Max	180	90	70,000	6
AutoBot v7	170	88	65,000	4.5
NanoDrive R3	160	92	85,000	3.5

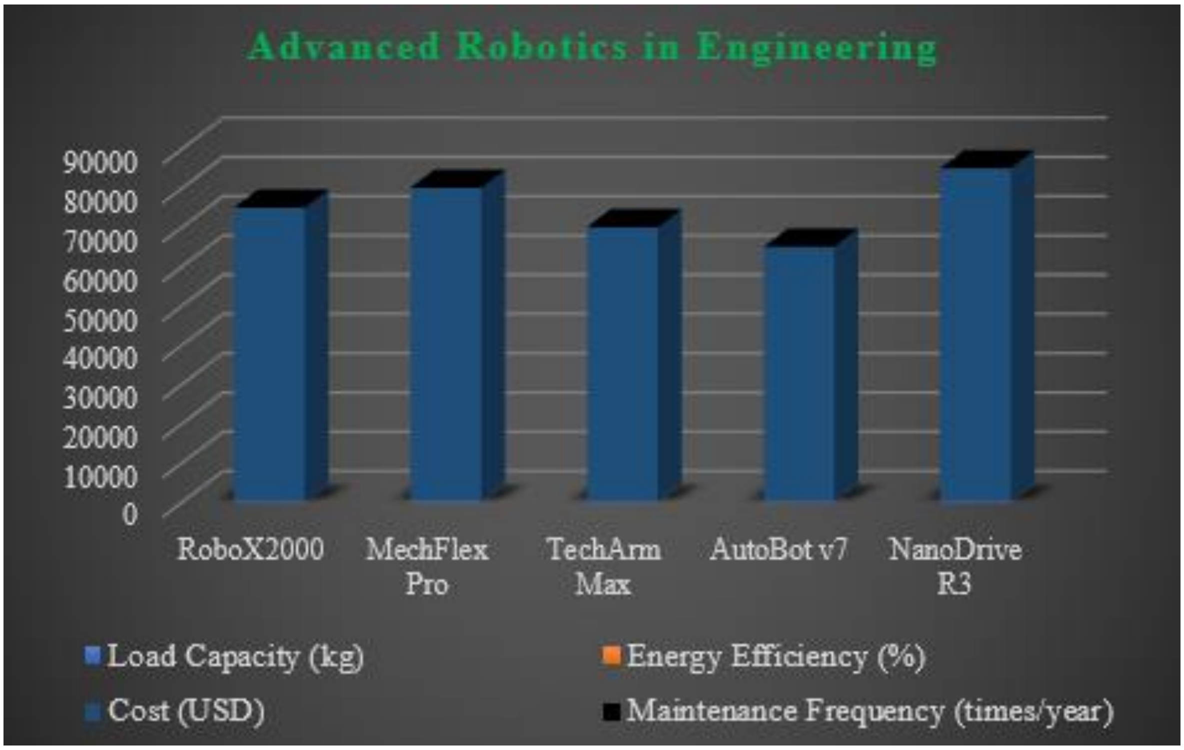

Fig. 1. Index plots depicting the hidden states characteristics for the two cluster types.

Table 2. Normalized Data.

Normalized Data				
	Load Capacity (kg)	**Energy Efficiency (%)**	**Cost (USD)**	**Maintenance Frequency (times/year)**
RoboX2000	0.17	0.20	0.20	0.22
MechFlex Pro	0.23	0.18	0.21	0.17
TechArm Max	0.21	0.21	0.19	0.26
AutoBot v7	0.20	0.20	0.17	0.20
NanoDrive R3	0.19	0.21	0.23	0.15

The blue bars represent the Load Capacity, indicating that MechFlex Pro has the highest capacity at 200 kg, while RoboX2000, TechArm Max, and others are lower in comparison. The cost parameter, represented by dark blue bars, shows that NanoDrive R3 is the most expensive, while AutoBot v7 is the least costly option. Energy efficiency, denoted by orange markers, highlights NanoDrive R3 as the most energy-efficient at 92%, followed by AutoBot v7 and TechArm Max. Lastly, Maintenance Frequency, represented in black, illustrates that NanoDrive R3 requires the least maintenance at 3.5 times/year, suggesting higher reliability compared to others. This figure summarizes the trade-offs among the robotic systems, revealing that NanoDrive R3 excels in terms of energy efficiency and reliability but comes with higher costs, while AutoBot v7 offers a cost-effective solution with lower performance in other parameters.

Table 2 presents the normalized data for five advanced robotic systems RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7, and NanoDrive R3 based on the COPRAS (COmplex PRoportional ASsessment) method. The data has been normalized across four key parameters: Load Capacity (kg), Energy Efficiency (%), Cost (USD), and Maintenance Frequency (times/year), with each value proportionally scaled to facilitate direct comparison. In terms of Load Capacity, MechFlex Pro shows the highest normalized value of 0.23, reflecting its advantage in handling larger loads. TechArm Max follows closely at 0.21, while RoboX2000 has the lowest normalized value of 0.17, indicating lower load capacity in comparison. For Energy Efficiency, TechArm Max and NanoDrive R3 exhibit the highest values at 0.21, indicating superior energy performance. RoboX2000 and AutoBot v7 are close behind at 0.20, while MechFlex Pro shows a slightly lower efficiency at 0.18. When considering Cost, NanoDrive R3 is the most expensive with a normalized value of 0.23, while AutoBot v7 is the least costly at 0.17, reflecting its cost-efficiency. Regarding Maintenance

Frequency, NanoDrive R3 requires the least maintenance, with a value of 0.15, making it the most reliable. In contrast, TechArm Max has the highest maintenance frequency with a normalized value of 0.26, indicating a higher maintenance requirement. Overall, NanoDrive R3 excels in energy efficiency and reliability, while MechFlex Pro is ideal for heavy load capacity. AutoBot v7 offers a cost-effective option with moderate performance across parameters.

Figure 2 presents the normalized data for five robotic systems—RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7, and NanoDrive R3—based on the COPRAS (COmplex PRoportional ASsessment) method. The graph shows the normalized performance of each system for four key parameters: Load Capacity (kg), Cost (USD), Energy Efficiency (%), and Maintenance Frequency (times/year). The lines represent the proportionate values, providing a comparative visual of how each system performs relative to others. The Load Capacity (blue line) peaks for MechFlex Pro, indicating its superiority in handling larger loads. The Cost (grey line) is relatively high for NanoDrive R3, as it is the most expensive, while AutoBot v7 demonstrates the lowest cost. The Energy Efficiency (orange line) peaks for NanoDrive R3, underscoring its significant advantage in energy savings, while other alternatives show lower but comparable efficiencies. The Maintenance Frequency (yellow line) peaks for TechArm Max, indicating a higher need for maintenance compared to others, whereas NanoDrive R3 requires the least maintenance, reflecting its reliability. The figure clearly demonstrates that NanoDrive R3 excels in energy efficiency and reliability, while MechFlex Pro stands out for load capacity. AutoBot v7, on the other hand, offers the most cost-effective solution but compromises on other key performance metrics.

For the weightages assigned to the evaluation criteria in the COPRAS (COmplex PRoportional ASsessment) method for five advanced robotic systems, each parameter Load Capacity (kg), Energy Efficiency (%), Cost (USD), and Maintenance Frequency (times/year) has been given an equal weightage of 0.25. This uniform distribution indicates that all four criteria are considered equally important in the assessment. The equal weighting ensures that no single factor dominates the decision-making process, allowing for a balanced comparison of the robotic systems across performance, cost, and maintenance considerations. This approach highlights the trade-offs without prioritizing any specific metric.

Table 3 presents the weighted normalized decision matrix for five robotic systems RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7, and NanoDrive R3 based on the COPRAS (COmplex PRoportional ASsessment) method. The matrix includes the weighted values for Load Capacity (kg), Energy Efficiency **(%)**, Cost (USD), and Maintenance Frequency (times/year), each parameter weighted equally with a factor of 0.25. For Load Capacity, MechFlex Pro leads with a weighted score of 0.058, indicating its high load handling capability, followed by TechArm Max at 0.052. RoboX2000 and NanoDrive R3 have slightly lower values, suggesting moderate load capacities. In terms of Energy Efficiency, NanoDrive R3 scores the highest at 0.05287, reflecting its superior energy-saving performance. TechArm Max also performs well with 0.05172, while MechFlex Pro is slightly behind at 0.04598. Regarding Cost, all systems except AutoBot v7 score 0.05, while NanoDrive R3 shows the highest cost impact with a value of 0.06, indicating that it is the most expensive. Finally, for Maintenance Frequency, TechArm Max requires the most maintenance, as reflected in its highest weighted score of 0.07. MechFlex Pro and NanoDrive R3 have the lowest values at 0.04, indicating lower maintenance needs and higher reliability. Overall, NanoDrive R3 excels in energy efficiency and reliability, while MechFlex Pro offers the best load capacity, with TechArm Max balancing between load and energy but with higher maintenance. AutoBot v7 provides a cost-effective option with moderate performance.

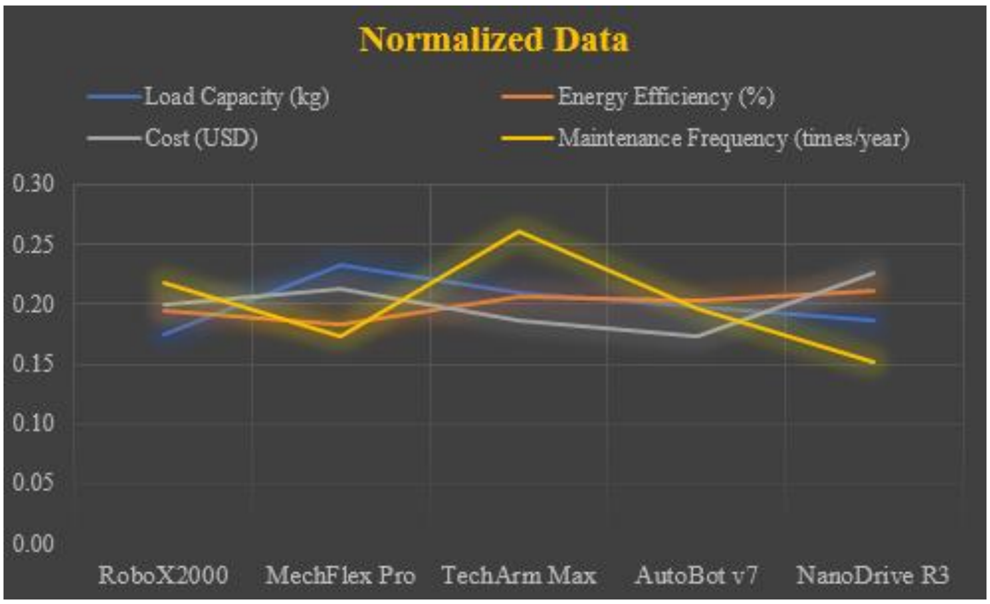

Fig. 2. Normalized Data.

Table 3. Weighted normalized decision matrix.

Weighted normalized decision matrix				
	Load Capacity (kg)	**Energy Efficiency (%)**	**Cost (USD)**	**Maintenance Frequency (times/year)**
RoboX2000	0.044	0.04885	0.05	0.05
MechFlex Pro	0.058	0.04598	0.05	0.04
TechArm Max	0.052	0.05172	0.05	0.07
AutoBot v7	0.049	0.05057	0.04	0.05
NanoDrive R3	0.047	0.05287	0.06	0.04

Table 4. Advanced Robotics in Engineering BI, CI, and Min(CI)/CI.

	BI	CI	Min(CI)/CI
RoboX2000	0.092	0.104	0.8840
MechFlex Pro	0.104	0.097	0.9528
TechArm Max	0.104	0.112	0.8245
AutoBot v7	0.100	0.092	1.0000
NanoDrive R3	0.099	0.095	0.9740
	min(CI)*sum(CI)	0.0461	4.6353

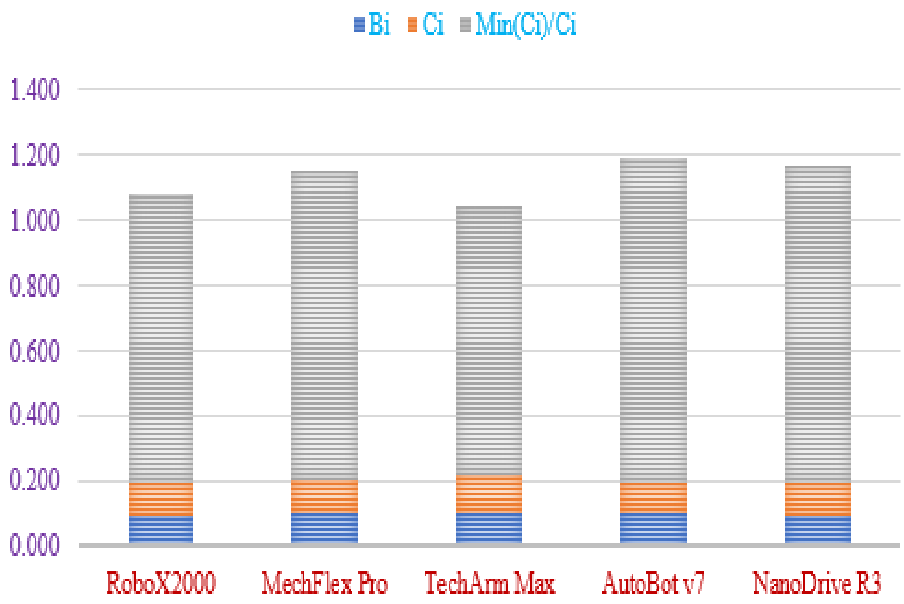

Fig. 3. Advanced Robotics in Engineering BI, CL, & Min (CI/CI).

Table 4 presents the BI (Benefit Index), CI (Cost Index), and Min(CI)/CI ratio for five robotic systems RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7**,** and NanoDrive R3 using the COPRAS (COmplex PRoportional ASsessment) method. These values provide insight into the overall benefit, cost-effectiveness, and proportional efficiency of each alternative. In terms of the Benefit Index (BI), MechFlex Pro and TechArm Max both score the highest at 0.104, indicating that these systems offer the best overall benefits compared to the other alternatives. AutoBot v7 follows closely at 0.100, while NanoDrive R3 and RoboX2000 have slightly lower BI values of 0.099 and 0.092, respectively. For the Cost Index (CI), AutoBot v7 stands out as the most cost-effective option with a CI of 0.092, indicating the lowest relative cost among all systems. TechArm Max has the highest CI at 0.112, suggesting it is the least cost-efficient. RoboX200**0** and NanoDrive R3 display moderate values, while MechFlex Pro achieves a favorable balance with a CI of 0.097. The Min (CI)/CI ratio indicates cost-effectiveness relative to the least costly option. AutoBot v7 scores a perfect 1.0000, making it the most cost-efficient. NanoDrive R3 follows closely with 0.9740, while TechArm Max has the lowest ratio at 0.8245, reflecting its higher cost impact relative to benefits. Overall, MechFlex Pro and NanoDrive R3 balance benefits and costs well, while AutoBot v7 offers the best cost-effectiveness despite lower overall benefits.

Figure 3 illustrates the comparative evaluation of five advanced robotic systems RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7, and NanoDrive R3 using the COPRAS (COmplex PRoportional ASsessment) method, with a focus on three key metrics: Bi**,** Ci, and Min(Ci)/Ci**.** The Bi (blue) represents the overall benefit index, while Ci (orange) stands for the cost index. The Min**(**Ci)/Ci ratio (grey) reflects the proportional balance between the lowest and highest cost-effectiveness values for each alternative. From the figure, it is clear that all five robotic systems exhibit similar patterns in terms of the Min(Ci)/Ci ratio (grey), indicating a relatively balanced cost-effectiveness across the alternatives. MechFlex Pro and NanoDrive R3 show the highest overall performance, as their stacked bar heights for Bi and Min (Ci)/Ci are marginally higher than the other systems. RoboX2000 and AutoBot v7 display comparatively lower benefit indices (Bi**),** which suggests they may be less effective in meeting benefit-related criteria. The Ci values (orange) remain proportionally consistent across all alternatives, indicating that the cost factors are relatively similar when compared against the Bi. Overall, MechFlex Pro and NanoDrive R3 emerge as the most balanced options, offering both strong benefits and reasonable costs, while AutoBot v7 remains a cost-effective but lower-performing option in terms of overall benefits.

Table 5 presents the final ranking of five advanced robotic systems RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7, and NanoDrive R3 using the COPRAS (COmplex PRoportional ASsessment**)** method, based on their QI (Quality Index), UI (Utility Index), and overall Rank. AutoBot v7 secures the top spot with a QI of 0.208 and a UI of 100%, indicating that it delivers the highest quality and overall performance among the alternatives. It is the most optimal choice in terms of both benefits and cost-effectiveness, reflecting its efficiency across the evaluation parameters. MechFlex Pro follows closely in second place with a QI of 0.207 and also achieves a UI of 100%. Despite its strong performance, it ranks slightly below AutoBot v7, likely due to minor differences in cost or maintenance. NanoDrive R3 ranks third, with a QI of 0.204 and a UI of 98%, showing a balanced mix of high energy efficiency, low maintenance, and moderate costs. Its high overall utility makes it a competitive option for those seeking energy-efficient solutions. TechArm Max ranks fourth with a QI of 0.193 and a UI of 93%, indicating solid performance but slightly higher maintenance and lower cost-effectiveness. Finally, RoboX2000 ranks fifth with a QI of 0.188 and a UI of 90%, showing the lowest overall performance, likely due to its moderate load capacity and higher costs.

Table 5. Final Result of Advanced Robotics in Engineering.

	QI	UI	RANK
RoboX2000	0.188	90%	5
MechFlex Pro	0.207	100%	2
TechArm Max	0.193	93%	4
AutoBot v7	0.208	100%	1
NanoDrive R3	0.204	98%	3

Figure 4 illustrates the QI (Quality Index) and UI (Utility Index) values for five advanced robotic systems—RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7, and NanoDrive R3—using the COPRAS (COmplex PRoportional ASsessment) method. The blue bars represent the QI values, and the orange line indicates the corresponding UI percentages for each robot. The highest QI score is held by AutoBot v7 at 0.208, followed closely by MechFlex Pro with a QI of 0.207, and these two models also achieve the top UI of 100%.

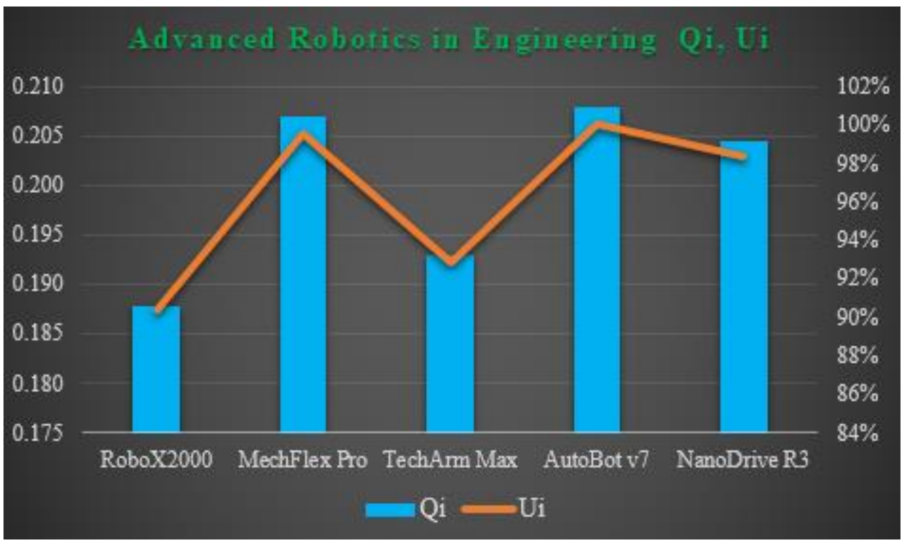

Fig. 4. Advanced Robotics in Engineering QI, UI.

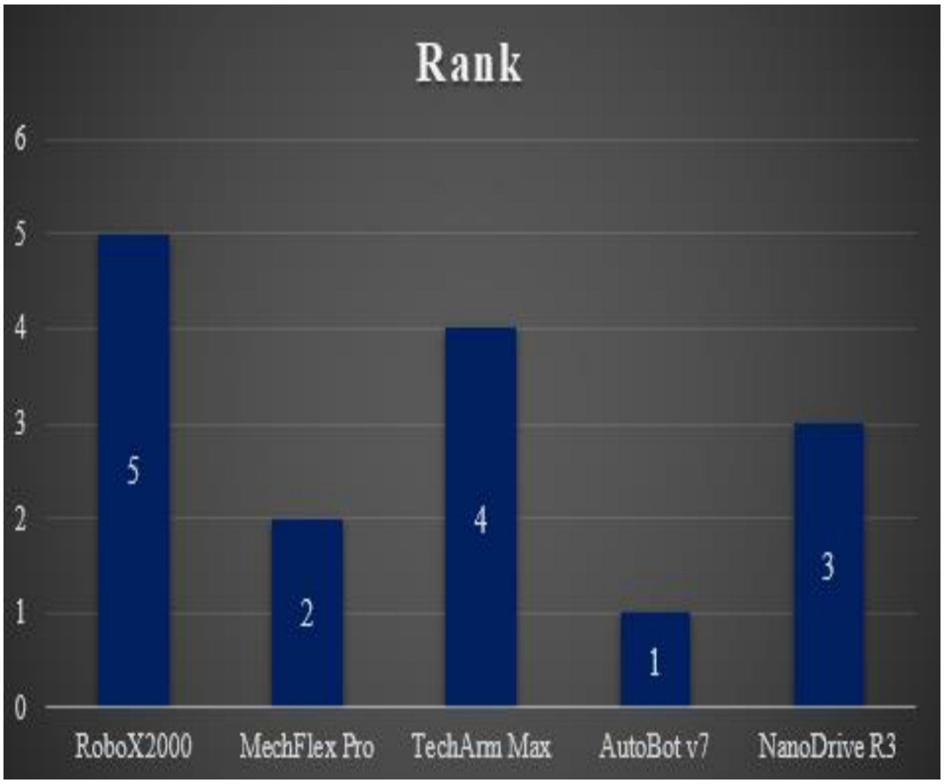

Fig. 5. Diagram for the Rank.

This reflects their superior performance and optimal balance between benefits and costs, making them the most favorable choices for advanced engineering applications. NanoDrive R3 also performs well, with a QI of 0.204 and a UI of 98%, indicating strong overall utility. Its slightly lower UI relative to the top performers is likely due to its higher cost, even though it excels in energy efficiency and reliability. TechArm Max shows a moderate performance, with a QI of 0.193 and a UI of 93%, while RoboX2000 ranks lowest with a QI of 0.188 and a UI of 90%, suggesting that it is less competitive in terms of load capacity and cost-effectiveness. Overall, AutoBot v7 and MechFlex Pro stand out as the best options, while RoboX2000 offers the least utility.

Figure 5 displays the rankings of five advanced robotic systems RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7, and NanoDrive R3 based on the COPRAS (COmplex PRoportional ASsessment) method. The rankings are determined by evaluating multiple criteria such as load capacity, energy efficiency, cost, and maintenance frequency. The highest-ranked system is AutoBot v7, which holds the 1st position. This confirms that AutoBot v7 is the most optimal choice in terms of balancing both performance and cost-effectiveness. Its low cost and efficient maintenance make it highly favorable for advanced engineering applications. In 2nd place is MechFlex Pro, showing strong performance across the board, particularly in load capacity and reliability, but slightly behind AutoBot v7 in terms of overall utility and cost-efficiency. NanoDrive R3 ranks 3rd, indicating that while it excels in energy efficiency and low maintenance, its higher cost might have negatively affected its overall ranking. TechArm Max comes in 4th, likely due to higher maintenance frequency and slightly higher costs, despite its strong energy efficiency and load capacity. Finally, RoboX2000 ranks the lowest at 5th, likely due to its moderate performance across the key parameters, including higher costs and maintenance frequency compared to its counterparts. Overall, this figure provides a clear overview of the competitive standing of each robotic system, with AutoBot v7 emerging as the top-performing solution.

5. CONCLUSION

This study provides a comprehensive evaluation of five advanced robotics systems RoboX2000, MechFlex Pro, TechArm Max, AutoBot v7, and NanoDrive R3 for engineering applications using the COPRAS (COmplex PRoportional ASsessment) method. By examining four benefit and four non-benefit criteria, including load capacity, energy efficiency, cost, and maintenance frequency, this research identifies the most optimal robotic system for advanced engineering tasks. The COPRAS method proved instrumental in processing these multiple criteria, allowing a balanced and objective comparison of the alternatives. The results highlight AutoBot v7 as the top-performing system, ranked first with the highest QI (Quality Index) of 0.208 and a perfect UI (Utility Index) of 100%. This demonstrates AutoBot v7's optimal balance of high energy efficiency, low cost, and low maintenance frequency, making it the most efficient and cost-effective solution for engineering projects. Its exceptional performance, particularly in cost savings, suggests that it is the most economically viable option for long-term use in advanced robotics applications. MechFlex Pro ranks second with a QI of 0.207 and a UI of 100%, closely following AutoBot v7. Its superior load capacity makes it suitable for applications requiring heavy lifting, though its slightly higher cost compared to AutoBot v7 positions it as a competitive but more expensive option. NanoDrive R3 ranks third with a UI of 98%, excelling in energy efficiency and low maintenance frequency but offset by its higher purchase cost, which slightly reduces its overall ranking. On the lower end of the ranking spectrum, TechArm Max and RoboX2000 rank fourth and fifth, respectively. TechArm Max achieves a QI of 0.193 and a UI of 93%, indicating that its relatively high maintenance frequency and moderate cost reduce its overall competitiveness. RoboX2000, with a QI of 0.188 and a UI of 90%, is the least favorable option, primarily due to its moderate performance across all parameters, particularly its cost and maintenance requirements. The COPRAS method has proven to be an effective tool for evaluating complex decision-making scenarios in advanced robotics. By providing a structured approach to multi-criteria analysis, it enables decision-makers in the engineering field to identify the most suitable robotic solutions based on various performance indicators. This study shows that AutoBot v7 and MechFlex Pro are the best-suited options, offering a superior balance of performance, cost, and efficiency for engineering applications.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests.

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