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Optimizing Agricultural Decision-Making with Artificial Intelligence: A COPRAS-Based Evaluation

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Abstract: *Artificial intelligence (AI) in agriculture has the potential to revolutionize farming practices, improving productivity, sustainability, and decision-making. This study explores the application of AI in agriculture, focusing on how AI-driven tools and systems can optimize various farming processes, such as crop management, pest control, and yield prediction. The research evaluates the role of AI in addressing challenges faced by farmers and its impact on agricultural efficiency. The findings highlight the significant benefits of AI technologies in modernizing agriculture and creating sustainable farming solutions. Research Significance: The significance of this research lies in its ability to showcase the transformative potential of artificial intelligence in agriculture. AI applications can enhance precision farming, reduce resource wastage, and improve crop yields, all of which contribute to better sustainability and profitability for farmers. The study explores how AI technologies can address key challenges in agriculture, such as labor shortages, unpredictable weather patterns, and the need for optimized resource use. The findings offer valuable insights into how AI can drive agricultural innovation and help ensure food security in an increasingly volatile global environment. Methodology: COPRAS The COPRAS (Complex Proportional Assessment) methodology is utilized to assess and compare various AI-driven agricultural solutions and technologies. By evaluating multiple alternatives based on their effectiveness in improving agricultural practices, COPRAS provides a structured approach to selecting the most suitable AI solutions. The methodology takes into account factors such as cost-effectiveness, efficiency, and scalability, helping to identify the most impactful AI technologies for different agricultural needs. Alternative: AI-based crop monitoring systems, AI-driven irrigation technologies, AI-powered pest detection tools, AI-enhanced yield prediction models, AI-assisted supply chain management. Evaluation Parameters: Product price (C1), Company rating (C2), Delivery time (C3), Transportation costs (C4). Result: The results of the COPRAS analysis demonstrate that AI-driven technologies have the potential to significantly improve agricultural outcomes. AI-powered systems that offer efficient crop monitoring, precise irrigation, and early pest detection provide high value to farmers. Technologies with lower costs and faster deployment times, such as AI-based irrigation systems, tend to rank higher in the evaluation, making them more attractive to farmers seeking affordable solutions. However, the effectiveness and scalability of the solution are also crucial factors influencing the overall ranking.*

Keywords: *Artificial intelligence, agriculture, precision farming, AI technologies, crop monitoring, irrigation systems, yield prediction, sustainability.*

1. INTRODUCTION

Insect pest attacks pose a significant threat to agriculture, resulting in significant economic losses. For decades, researchers have been working to solve this problem by developing computerized systems capable of detecting active pests and recommending appropriate control measures. Soil and irrigation management play a crucial role in agriculture. Poor management in these areas can result in crop losses and a decline in quality. Furthermore, in the era of precision agriculture, predictive models can be used to analyze key factors that directly affect crop yields. This shift is towards automated and precise systems that operate in real time. Ongoing research using advanced tools aims to transform traditional agriculture into precision agriculture at a lower cost. This literature review highlights 100 significant contributions where AI techniques have been used to address agricultural challenges.[1] The integration of AI in agriculture will be facilitated by advances in various technologies such as big data analytics, robotics, IoT, affordable sensors and cameras, drone technology, and widespread internet access in vast agricultural areas. The development of expert systems for agriculture is relatively new and their adoption in commercial agriculture is low. In this context, it is essential to use the latest technological advances to improve agricultural efficiency. Current approaches to increasing agricultural production rely on significant energy inputs, while market expectations emphasize the need for high-quality food.[2] Additional funding will be needed beyond the expected investments in agriculture; otherwise, about 370 million people will face hunger. The current state of artificial intelligence in agriculture is examined with an emphasis on three key aspects and developments: soil management, weed control, and the integration of the Internet of Things (IoT). Soil plays a vital role in successful farming, serving as the primary source of essential nutrients. It contains water, nitrogen, phosphorus, potassium, and proteins, all of which are essential for healthy crop growth and development. IoT has various applications in agriculture, including surveillance, precision farming, tracking and tracing, greenhouse management, and agricultural machinery operation. AI plays a significant role in robotics, especially in agriculture, where efforts have been made for years to integrate robotic systems to improve efficiency, reliability, and accuracy.[3] These AI-driven technologies collect detailed and accurate data on crop health for analysis. This study explores the role of AI in agriculture, outlining its processes and the key agricultural parameters it monitors. Finally, significant AI applications in agriculture are identified and discussed. Farmers can use machine learning in precision agriculture to strategically apply agrochemicals, taking into account the time, location, and specific crops affected. AI offers a wide range of applications in agriculture, enabling precision farming. Using data from various sources, AI assists farmers in tasks such as irrigation, crop rotation, harvesting, crop selection, planting, and pest management. Researchers and agricultural extension experts are now using AI technology to address challenges related to agricultural productivity.[4] Artificial Intelligence (AI) has transformed agriculture, protecting crop production from various challenges including climate conditions, population growth, labor concerns, and food security issues. A key aspect of this transformation is the various applications of AI in agriculture, such as irrigation, weeding, and spraying, the use of sensors, and automated systems such as robots and drones. This is the impact of AI on agriculture. While AI offers significant benefits, technology companies still have considerable work to do to ensure farmers effectively adopt and implement it. The real purpose of data collection and generation is to use it effectively. In agriculture, data analysis can lead to significant increases in productivity and significant cost savings. Precision farming, a modern farm management approach, helps farmers achieve higher yields using fewer resources. With the support of AI, precision farming has the potential to revolutionize the agricultural sector.[5] As the initial aim of this review, we will provide a brief introduction to these topics for readers with a background in agriculture and food science. The applications selected for discussion are based on our experiences and their significant impact on the global agriculture and food sector. It is important to note that data can originate from a variety of sources, including agriculture, food processing, manufacturing, supply chains, diagnostic systems, and consumers. While IoT sensors serve as data collection points in agriculture, consumer data is often collected through comments shared on social media platforms. Precision agriculture (PA) is an agricultural approach that acknowledges variations in soil environments, aiming to improve agricultural productivity while minimizing environmental impact to a specific location. The primary advantage of this technology is its ability to reduce the use of agricultural chemicals, leading to economic savings and environmental benefits.[6] AI is becoming accessible to agricultural businesses due to advances in AI research, growing investments in AI solutions, significantly improved computing power, and affordable access to computing and cloud technologies. Digital or smart farming aims to improve precision farming by incorporating advanced digital solutions, including AI, to drive progress in the agricultural sector. As a result, AI in agriculture serves as a key tool in precision farming and smart farming, helping to meet the growing demand for food while ensuring profitability and industry growth. We also aim to assess the extent to which interdisciplinary collaboration and solutions are needed to address the regulatory challenges highlighted in the literature. Our findings are incorporated into a proposed interdisciplinary approach to implementing AI in agriculture. Real-time data, enabled by the Internet of Things and cloud computing, is used to support a variety of agricultural domains, including soil management, pest and weed control, disease prevention, crop management, and water-use optimization. A major cash crop for farmers in both developed and developing countries, it is currently harvested using machinery such as strippers or spindle pickers in developed countries, while manual harvesting is common in developing areas. [7,8] Artificial intelligence, a major technological advancement, is revolutionizing the agricultural sector by improving resource consumption and utilization. Agriculture is a multidisciplinary field that encompasses scientific, engineering, and economic aspects. AI has made significant contributions to this field, with many studies dedicated to its advancement. Comparable studies in the agri-food industry and agriculture are relatively rare and undocumented. However, interest in both fields has increased significantly. The use of AI in agriculture is becoming increasingly widespread, covering various aspects of the sector and connecting it to many related areas. An analysis of the most impactful journals addressing AI applications in agriculture reveals a diverse range of publications covering multiple knowledge areas. To assess the overall strength of co-authorship connections, a minimum threshold of two published articles per author was established.[9] The intensification of agriculture is placing considerable pressure on energy resources, primarily fossil fuels, with demand expected to be low within the next 15-20 years unless substantial measures and investments are implemented globally. This study focused on three main types of intelligent agents: expert systems and agriculture-specific software, specialized sensors for data collection and transmission, and robotic and automated systems used in agriculture. The accuracy and performance of these systems are not yet sufficient to integrate them into a fully functional expert system for agriculture. However, current research efforts are actively working on improving these technologies. Various specialized sensors are now widely used in agriculture, often integrated with advanced agricultural machinery or installed in farm structures and the areas around them.[10] The anomalies in the grape plants were only detected after the infection had already occurred, significantly affecting the entire vineyard. The system used various sensors, including temperature, leaf wetness and humidity sensors, to monitor conditions. These sensors sent the collected data to a database on a ZigBee server, which was connected to them. Embedded intelligence in the agricultural sector encompasses smart farming, advanced crop management, intelligent irrigation, and automated greenhouse systems. The application of robotics in agriculture involves designing robots that follow a white line, marking designated work areas, while other surfaces, such as black or brown, are recognized as no-go zones. Several companies have introduced sensor-based smart irrigation systems designed to optimize water use, monitor water pollution, and address other critical challenges in agriculture.[11] Agriculture has evolved into a commercial hub, prompting farmers to embrace precision farming. They have integrated technology into agriculture to gain accurate information about seeds, soil, weather, diseases, and other factors that affect farming. AI-driven companies are developing robots capable of efficiently performing multiple tasks in the agricultural sector. These robotic machines are designed to manage weeds and harvest crops, significantly faster and at a higher volume than human labor. Artificial intelligence technologies are having a significant impact on the agricultural sector. This section highlights several AI methods and techniques that are closely related to agriculture.[12]

2. MATERIALS AND METHOD

Alternatives: Supplier S1: Precision Farming Equipment Supplier: For Supplier S1, which provides precision farming equipment, AI can be used to enhance the accuracy of farming machinery. AI-powered systems can help optimize planting, fertilization, irrigation, and pesticide application by analyzing environmental data in real time. This allows farmers to use resources more efficiently, reduce costs, and increase yields. For example, AI can guide tractors to plant seeds at optimal depths and distances, improving crop growth and reducing waste. Supplier S2: Seed Supplier: Supplier S2, a seed supplier, can leverage AI to predict the best seed varieties for specific environmental conditions, taking into account factors like soil type, weather patterns, and historical crop performance. AI-powered systems can analyze large datasets to provide farmers with the most suitable seed recommendations, enhancing crop yields and reducing the likelihood of crop failure. AI can also assist in the development of genetically modified seeds that are more resistant to diseases, pests, and environmental stressors. Supplier S3: Fertilizer and Agrochemical Supplier: For Supplier S3, which deals with fertilizers and agrochemicals, AI can be used to create precision application systems. By utilizing machine learning models, AI can predict the optimal amount of fertilizer and pesticide required for different sections of a farm, reducing overuse and minimizing environmental impact. AI algorithms can also help detect early signs of pest infestations and diseases, allowing suppliers to deliver targeted solutions to farmers and improve crop protection. Supplier S4: Irrigation System Supplier: Supplier S4, which specializes in irrigation systems, can benefit from AI through smart irrigation solutions that monitor soil moisture, weather conditions, and crop needs. AI can help automate irrigation schedules based on real-time data, ensuring that crops receive the right amount of water at the right time, thus optimizing water use and improving crop health. In regions with water scarcity, AI-driven irrigation systems can significantly reduce water waste and improve sustainability. Supplier S5: Farm Equipment Maintenance Supplier: Supplier S5, focused on farm equipment maintenance, can use AI to offer predictive maintenance services. AI can monitor farm machinery and equipment, analyzing data from sensors embedded in machines to predict when parts are likely to fail. By performing maintenance before a breakdown occurs, suppliers can reduce downtime, extend the life of equipment, and ensure that farmers have reliable machinery during critical periods of the growing season.

Evaluation parameter: Product Price (C1): When adopting AI technologies in agriculture, the cost of products is a crucial factor for decision-making. AI-driven equipment, sensors, or software solutions can have varying price points depending on their complexity and the level of automation they provide. Suppliers offering AI-powered solutions should ensure that their products are priced competitively to make them accessible to farmers across different regions and income levels. The cost of AI solutions should also reflect the potential savings and yield improvements these products can deliver over time. Farmers will evaluate whether the long-term benefits—such as increased crop yield, resource optimization, and reduced input costs—outweigh the initial investment. Company Rating (C2): Company ratings and reviews play an important role in the selection process. A supplier's reputation can provide valuable insight into the reliability, quality, and customer service associated with their products. AI in agriculture is a relatively new field, and farmers may prefer working with companies that have a proven track record of successful AI applications in agriculture. Higher-rated companies are often trusted for providing cutting-edge technology and effective solutions, with excellent post-purchase support and technical assistance. Farmers may also look for endorsements from agricultural industry experts, certifications, or successful case studies before choosing a supplier. Delivery Time (C3): The delivery time for AI-powered agricultural products is a key factor in ensuring that farming operations run smoothly, especially when time-sensitive activities such as planting, irrigation, or harvesting are involved. Suppliers that offer quick delivery times for their AI solutions, particularly when addressing urgent needs or seasonal demands, have a competitive edge. Efficient delivery times reduce downtime for farmers and ensure that they can start using the AI technology as soon as possible to enhance productivity. Furthermore, suppliers that offer flexible delivery options, including installation and setup services, add further value to their offerings. Transportation Costs (C4): Transportation costs can significantly impact the overall expense of AI solutions, particularly for larger equipment or systems that require shipping over long distances. High transportation costs could make AI technologies less affordable, especially for farmers in remote areas or regions with limited logistics infrastructure. Evaluating the transportation costs from suppliers is important as it can influence the total cost of ownership for AI products. Suppliers offering cost-effective and efficient transportation solutions, or those with local distribution networks, may provide more attractive pricing options for farmers.

COPRAS: The authors attempt to address this issue by proposing a set of criteria that directly and proportionally assess the suitability and effectiveness of the alternatives under consideration, along with their associated values and weights. The research uses COPRAS techniques, explains how the three MHE cases were selected, and incorporates computational data in the process. The results highlight the main findings of the study, followed by a comparison of these results with previous research, as well as a sensitivity analysis to assess the consistency and robustness of MCDM methods. The study concludes with a discussion of its findings, including a definition of COPRAS, its application, and an examination of its consistency with respect to data variations. The article examines methods for estimating hierarchically structured composite numerical criteria on a single scale, using both SAW and COPRAS. Each theoretical statement is supported by calculations and examples. As a result, the rankings obtained may differ compared to rankings obtained by other methods, and COPRAS results may be sensitive to small changes in the data. This article explains how two data variances were calculated using COPRAS, showing cases where data changes can lead to instability in COPRAS, causing results to differ from those achieved by other multivariate estimation techniques. In addressing a real-time robot selection problem involving 12 alternative robots and five selection criteria, the criterion importance was used through the Inter-Criteria Correlation (CIC) weighting tool to evaluate the parameter importance of two hybrid models, TOPSIS-ARAS and COPRAS-ARAS. COPRAS uses an integrated evaluation framework that takes into account both cost and benefit criteria to evaluate alternatives. One of the main advantages that differentiates COPRAS from other MCDM methods is its focus on the level of utility of alternatives, which is expressed as a percentage to show how much better or worse an alternative is compared to others. The COPRAS method uses a stepwise ranking to assess the importance and utility of alternatives. After ranking each sub-district using three different methods, comparisons are made to identify the sub-district that is most suitable for mining operations. COPRAS is used to evaluate a multi-criteria system by optimizing both the maximum and minimum values, which makes it the preferred choice over other methods due to its ease in comparing and validating the measurement results. In addition, the method is useful for comparing and evaluating variables that are organized hierarchically. COPRAS can evaluate alternatives based on benefit (positive) and cost (negative) criteria, considering each separately for each alternative. A key advantage of the COPRAS approach is the ability to solve problems by taking into account the level of utility, which allows for a clear comparison of how alternatives perform. By providing estimates in intervals, the COPRAS method can conduct analyses of multiple alternatives and generate various calculations based on the level of utility. A shared common feature is that the actual data is transformed into broad ranges through normalization formulas. This step is important to mitigate the impact of high-value data on the final results after the analysis. Once the user has provided ratings for the alternatives, they can continue the calculation process using the COPRAS calculation form. The form guides the user through each step of the COPRAS calculation process, ultimately providing ranked results for the alternatives. COPRAS was selected for this task to identify and map potential Cu-target zones. One might question why this paper chose the HMCDM approach. Although there are many MCDM methods, whether general or specific, none can be considered the best for every decision-making situation. COPRAS was used to rank the alternatives, each clearly defined by the various variables that need to be considered together. Once the ranking process was finalized, the results were transferred to ArcGIS software. However, COPRAS lacks the ability to directly incorporate expert judgments, which can lead to an inaccurate perspective model. In addition, project managers should be aware that careful planning during the design phase of a manufacturing site can help reduce reengineering costs and operational waste. Beyond its theoretical and practical contributions, this study will also contribute to the development of a more efficient lean processing framework in the future. We also present an example demonstrating how the proposed entropy is utilized in decision-making analysis using the COPRAS method, with the new entropy applied. The results are then compared to existing methods, and their analysis is conducted using the WS and weighted Spearman Axioms coefficient. The findings indicate that the new entropy can seamlessly replace the old version. However, further research is needed for a complete comparison. The proposed entropy measure provides a new perspective on the COPRAS method in solving the MCDM problem. In the decision-making process for selecting the best household ceramics, the COPRAS technique involves collecting data on ceramic criteria, where the ceramic type is an alternative. Based on the previous problem formulation and research, the conclusion of this study is that the complex proportion evaluation (COPRAS) approach is capable of evaluating multiple options and ranking them according to their utility levels when attribute values are given in intervals. The research demonstrates that the application of the COPRAS approach in selecting the best household ceramics involves collecting data on ceramic criteria, where the ceramic type is considered an alternative. The study uses the AHP method to evaluate the importance of the criteria, while the COPRAS method is used to provide the final result. The analytical hierarchy process (AHP) compares the criteria using the Chatty scale, and the COPRAS method is used to find the best solution. The data collected from a questionnaire were analyzed using the COPRAS approach to determine the most appropriate strategy.

3. RESULT AND DISCUSSION

TABLE 1. Precision Farming Equipment Supplier

	product price (C1)	company rating (C2)	delivery time (C3)	transportation costs (C4)
Supplier S1	352.00	254.00	354.00	345.00
Supplier S2	241.00	684.00	145.00	440.00
Supplier S3	265.00	547.00	265.00	651.00
Supplier S4	451.00	254.00	245.00	245.00
Supplier S5	862.00	654.00	385.00	358.00

Table 1 provides a comparison of five suppliers (S1 to S5) based on four key evaluation criteria: product price (C1), company rating (C2), delivery time (C3), and transportation costs (C4). Product price (C1): Supplier S5 has the highest product price of 862, followed by Supplier S4 at 451. Supplier S2 offers the lowest price of 241, making it the most affordable option. Company rating (C2): Supplier S2 has the highest company rating of 684 with a strong customer rating. Supplier S1 and Supplier S4 both have a rating of 254, while Supplier S3 and Supplier S5 have ratings of 547 and 654, respectively. Delivery Time (C3): Supplier S2 offers the shortest delivery time at 145, which is the fastest in terms of delivery. Supplier S3 follows with a delivery time of 265, which is much longer than Supplier S2.

Supplier S1 and Supplier S5 have delivery times of 354 and 385, respectively, while Supplier S4 offers the shortest delivery time among the higher-priced options at 245. Supplier S1's transportation costs are 345, while Supplier S5 has moderate transportation costs of 358. Supplier S2 and Supplier S3 have high transportation costs of 440 and 651, respectively.

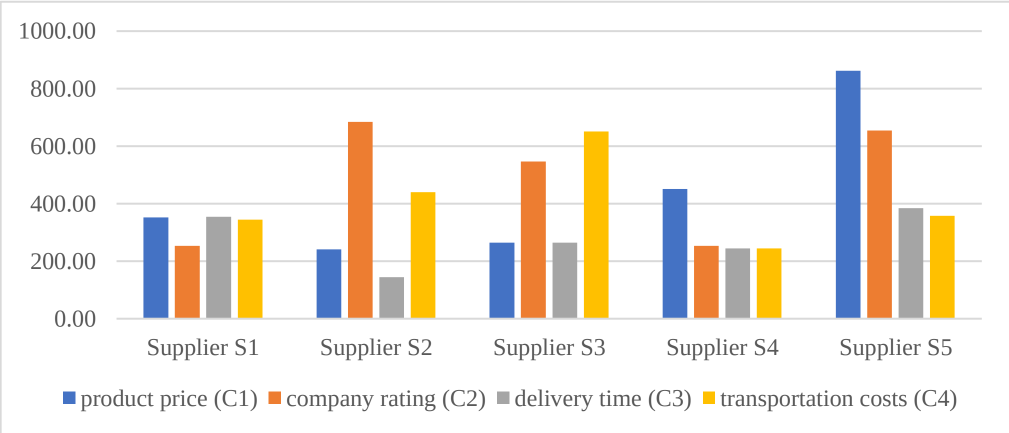

FIGURE 1. Precision Farming Equipment Supplier

Figure 1: Supplier Performance Comparison Across Multiple Criteria The chart displays a comprehensive comparison of five suppliers (S1-S5) evaluated across four key metrics: product price (C1), company rating (C2), delivery time (C3), and transportation costs (C4). Supplier S5 offers the highest product price but maintains strong company ratings, while Supplier S2 presents the highest company rating despite average product pricing. Supplier S3 stands out with the highest transportation costs. Delivery times appear most favorable for Supplier S2, indicated by the lower gray bar value. This multidimensional analysis reveals that each supplier presents distinct advantages and disadvantages across the evaluation criteria, suggesting that selection decisions should prioritize the most critical factors for specific business needs.

TABLE 2. Normalized Data

	product price (C1)	company rating (C2)	delivery time (C3)	transportation costs (C4)
Supplier S1	0.1621	0.1061	0.2539	0.1692
Supplier S2	0.1110	0.2858	0.1040	0.2158
Supplier S3	0.1221	0.2286	0.1901	0.3193
Supplier S4	0.2077	0.1061	0.1758	0.1202
Supplier S5	0.3971	0.2733	0.2762	0.1756

The normalized data presents various attributes of five suppliers (S1, S2, S3, S4, and S5) across four different factors: product price (C1), company rating (C2), delivery time (C3), and transportation costs (C4). Product Price (C1): The normalized price data indicates that Supplier S5 has the highest product price at 0.3971, while Supplier S2 has the lowest price at 0.1110. This suggests that Supplier S5 may offer more expensive products compared to others. Company Rating (C2): Supplier S2 has the highest company rating at 0.2858, implying that they are highly rated by customers or partners. Meanwhile, Supplier S1 and Supplier S4 both have the lowest company ratings at 0.1061, indicating that they may not be as highly regarded in terms of customer satisfaction or reputation. Delivery Time (C3): The delivery time varies among the suppliers, with Supplier S1 having the highest normalized delivery time at 0.2539, suggesting longer delivery times. Supplier S2 has the lowest delivery time at 0.1040, indicating a faster delivery compared to others. Transportation Costs (C4): Transportation costs are highest for Supplier S3 with a normalized value of 0.3193, suggesting that this supplier may have the most expensive transportation options. On the other hand, Supplier S4 has the lowest transportation cost at 0.1202, suggesting more affordable shipping rates.

TABLE 3. Weight

Weight			
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

The data presented represents a series of weights, each with a value of 0.25. This suggests that the weight is distributed evenly across multiple categories or elements. There are a total of 16 events, each with a weight of 0.25. These weights appear to be balanced, indicating that each element or factor has equal importance or contribution to the overall outcome, with no particular element being given priority or preference. This can be interpreted as a uniform distribution of importance, where each part has an equal share or weight.

TABLE 4. Weighted normalized decision matrix

	Weighted normalized decision matrix			
	product price (C1)	company rating (C2)	delivery time (C3)	transportation costs (C4)
Supplier S1	0.04	0.03	0.06	0.04
Supplier S2	0.03	0.07	0.03	0.05
Supplier S3	0.03	0.06	0.05	0.08
Supplier S4	0.05	0.03	0.04	0.03
Supplier S5	0.10	0.07	0.07	0.04

The data in Table 4 represents a weighted normalized decision matrix for assessing different suppliers based on four criteria: product price (C1), company rating (C2), delivery time (C3), and transportation costs (C4). Each supplier (S1 through S5) is rated according to these factors, with values ranging from 0.03 to 0.10, reflecting their relative performance or standing in each category. Supplier S1: This supplier has a relatively low rating across all criteria, with values of 0.04 for product price, 0.03 for company rating, 0.06 for delivery time, and 0.04 for transportation costs. It suggests that Supplier S1 has a balanced but modest performance, offering competitive product pricing and transportation costs but weaker company ratings and delivery times. Supplier S2: Supplier S2 performs well in company rating (0.07), suggesting a strong reputation, but has lower values in delivery time (0.03) and product price (0.03), along with moderate transportation costs (0.05). This could indicate that while Supplier S2 has a good reputation, it might not be the best option for price or delivery efficiency. Supplier S3: This supplier's performance is balanced with a slightly higher value in delivery time (0.05) and transportation costs (0.08). With values of 0.03 for both product price and company rating, Supplier S3 might offer reliable delivery but at a higher transportation cost, potentially making it less cost-effective for clients focused on price. Supplier S4: Supplier S4 stands out in product price (0.05) and delivery time (0.04), but has lower transportation costs (0.03), making it an attractive option for cost-conscious buyers. However, the company rating is lower at 0.03, possibly reflecting a weaker market reputation. Supplier S5: Supplier S5 has the highest value for product price (0.10), indicating it might be the most competitive in terms of cost. It also has solid performance in company rating (0.07) and delivery time (0.07), with average transportation costs (0.04). This suggests that Supplier S5 could be the most cost-effective choice, offering a good balance between price, rating, delivery, and costs.

TABLE 5. Bi and Ci

Bi	Ci
0.067	0.106
0.099	0.080
0.088	0.127
0.078	0.074
0.168	0.113

Table 5 presents two sets of values: Bi and Ci, each representing a specific measure or evaluation for five different entities or categories. These values are likely used to compare or assess the performance of these entities based on two distinct criteria or factors. For Bi, the values are as follows: 0.067, 0.099, 0.088, 0.078, and 0.168. These represent the first criterion, which could be an indicator such as performance, cost, or any other metric that needs to be evaluated. The highest value of 0.168 appears for the fifth entity, which may indicate the best performance or ranking in that particular measure. For Ci, the values are 0.106, 0.080, 0.127, 0.074, and 0.113. These values represent the second criterion, which might be another factor-like quality, efficiency, or customer satisfaction. The highest value in this set is 0.127 for the third entity, suggesting that this entity excels in the second criterion. The values in both sets can be used to make a comparative analysis. For example, if higher values in both Bi and Ci are desirable, the fifth entity (with Bi = 0.168 and Ci = 0.113) would likely be considered the most favorable option based on these metrics. Similarly, the third entity stands out in terms of Ci, but its Bi value is slightly lower than the others.

TABLE 6. Min (Ci)/Ci

	Min (Ci)/Ci
Supplier S1	0.6993
Supplier S2	0.9253
Supplier S3	0.5809
Supplier S4	1.0000
Supplier S5	0.6550

Table 6 presents the ratio Min (Ci)/Ci for five suppliers (S1 to S5). This ratio compares the minimum value of a criterion (Min (Ci)) to each individual supplier's value (Ci) for that criterion, and it can be used to evaluate the suppliers based on their relative performance in the context of the minimum value for that criterion. Supplier S1 has a ratio of 0.6993, meaning that its performance relative to the minimum value is moderately strong. It performs somewhat better than the worst-performing supplier for the criterion. Supplier S2 has the highest ratio of 0.9253, indicating that it is closest to the optimal performance or the minimum value in comparison to the other suppliers. This suggests Supplier S2 performs well relative to the benchmark. Supplier S3 has a ratio of 0.5809, which indicates its performance is relatively lower than others when compared to the minimum value. This might imply it is farther from the ideal performance. Supplier S4 has a ratio of 1.0000, which represents the best possible score in this comparison, suggesting that Supplier S4 is performing exactly at the minimum level of the benchmark, making it the most competitive or ideal in this context. Supplier S5 has a ratio of 0.6550, meaning its performance is somewhat below the best-performing suppliers but still better than some of the others.

TABLE 7. Qi and Ui

	Qi	Ui
Supplier S1	0.158	62.4516
Supplier S2	0.219	86.7783
Supplier S3	0.163	64.5352
Supplier S4	0.208	82.3962
Supplier S5	0.252	100.0000

Table 7 presents two sets of values: Qi and Ui, associated with five suppliers (S1 to S5). These values represent some form of evaluation or score for each supplier, with Qi and Ui potentially reflecting different criteria or performance metrics. Qi represents a quantitative measure, possibly related to an efficiency score, product quality, or another measurable factor. For example: Supplier S1 has a value of 0.158, indicating a lower score in comparison to other suppliers. Supplier S2 has a value of 0.219, showing a better performance than Supplier S1. Supplier S3 has a value of 0.163, which is slightly higher than S1 but lower than S2, placing it in the middle range. Supplier S4 has a value of 0.208, suggesting a performance level that is between S3 and S2. Supplier S5 has the highest value of 0.252, indicating the best performance in terms of the Qi measure among all the suppliers.

Ui represents a secondary evaluation or overall score, which might incorporate multiple factors, such as cost-effectiveness, customer satisfaction, or another aggregated performance metric. For example: Supplier S1 has an Ui value of 62.4516, suggesting a relatively lower overall performance compared to others. Supplier S2 scores 86.7783, showing a better overall score than Supplier S1, indicating a stronger performance in a broader evaluation. Supplier S3 has a value of 64.5352, which is slightly higher than Supplier S1 but still lower than Supplier S2, indicating moderate overall performance. Supplier S4 has a score of 82.3962, falling below Supplier S2 but higher than Supplier S3, suggesting a reasonably strong performance. Supplier S5 leads with an Ui value of 100.0000, representing the highest overall performance and possibly the best option based on this specific metric.

TABLE 8. Rank

	Rank
Supplier S1	5
Supplier S2	2
Supplier S3	4
Supplier S4	3
Supplier S5	1

Table 8 presents the ranking of five suppliers (S1 to S5), with each supplier assigned a rank based on their overall performance or evaluation. The ranking likely reflects their relative position or competitiveness in comparison to the others. Supplier S1 is ranked 5th, indicating that it performs the worst among the five suppliers. This suggests that Supplier S1 is the least favorable option when considering the factors being evaluated. Supplier S2 is ranked 2nd, indicating that it performs well, but not the best. It is a solid choice but not the top performer. Supplier S3 holds the 4th rank, meaning it performs better than Supplier S1 but not as well as Suppliers S2 and S4, placing it in the lower half of the rankings. Supplier S4 is ranked 3rd, which indicates a mid-tier performance. Supplier S4 is competitive but slightly behind Supplier S2. Supplier S5 is ranked 1st, marking it as the top-performing supplier. This suggests Supplier S5 is the most favorable option based on the criteria being assessed.

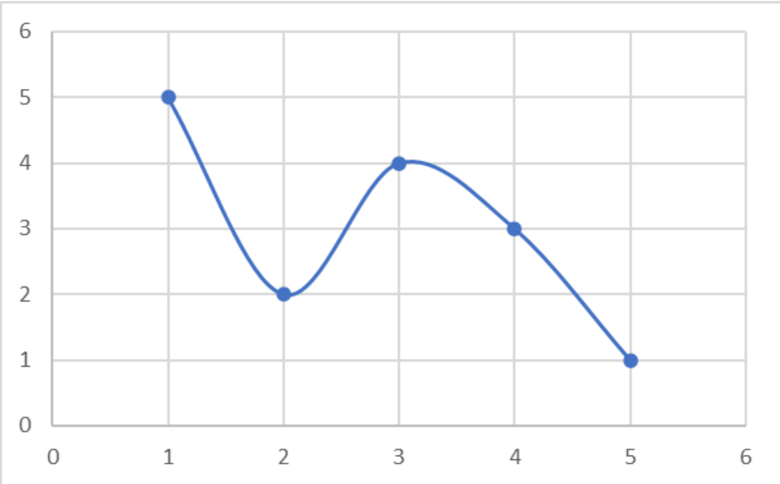

FIGURE 2. Rank

Figure 2: Fluctuation in Values Over a Five-Point Measurement Period The graph displays a notable wave pattern of measurements across five distinct data points. Starting at a high value of approximately 5 units at point 1, the curve experiences a sharp decline to 2 units at point 2, followed by a significant recovery to 4 units at point 3. The trend then reverses again, showing a steady descent through point 4 (approximately 3 units) before reaching its lowest value of 1 unit at point 5. This oscillating pattern suggests a cyclical phenomenon with alternating periods of increase and decrease, potentially indicating a natural fluctuation in the measured variable or the influence of periodic external factors on the system being studied.

4. CONCLUSION

In conclusion, the normalized data provides a clear comparative analysis of the five suppliers on four key attributes: product price, company rating, delivery time, and transportation costs. Supplier S5 stands out with the highest product price, suggesting that they may offer high-quality products but at a premium price. In contrast, Supplier S2 offers the lowest product price, making it an attractive option for price-conscious buyers. In addition, Supplier S2 also has the highest company rating, indicating that they have a positive reputation, providing reliable service and customer satisfaction. In terms of delivery time, Supplier S2 excels, offering fast delivery with the lowest normal score in this category.

This would make them the preferred choice for businesses that prioritize fast delivery. However, Supplier S1 has a relatively high normal delivery time, suggesting that customers may experience slower shipping speeds when choosing this supplier. Transportation costs are another important factor, with Supplier S3 having higher costs, which may appeal to those on a tight shipping budget. On the other hand, Supplier S4 offers lower transportation costs, which may be a deciding factor for customers looking to reduce overall costs.

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