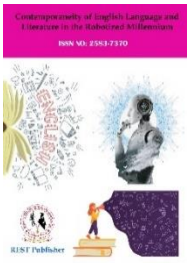
Contemporaneity of English Language and Literature in the Robotized Millennium
Vol: 4(3), September 2025
REST Publisher; ISSN: 2583 7370
Website: https://restpublisher.com/journals/cellrm/
DOI: https://doi.org/10.46632/cellrm/4/3/5



Multi-Criteria Evaluation for Selecting Medicine Providers: A Comprehensive Analysis Using COPRAS Method

Vidhya Prasanth, Chitra Periyasamy, M. Ramachandran, Manjula Selvam
REST Labs, Kaveripattinam, Krishnagiri, Tamil Nadu, India
*Corresponding author Email: prasanthvidhya69@gmail.com

Abstract: *The selection of medicine providers is a critical process, particularly in urgent situations such as responding to health crises or escalating demands. This study employs the COPRAS method to evaluate and prioritize five medicine providers based on essential criteria including reliability, quality, pricing, production capacity, technological expertise, unique medicine attributes, and delivery efficiency. Health tourism has seen a substantial surge, encompassing not only medical services but also accommodations, local attractions, transport, and dining options. Customers seek a method to choose healthcare destinations considering various factors. The focus on medical services, especially during emergencies like natural disasters or viral outbreaks, has prompted extensive research. This paper aims to use the COPRAS method, known for handling uncertain and incomplete data, to select medical providers for such critical situations. This method calculates criteria weights, manages uncertain evaluations from experts, and ranks feasible alternatives. By demonstrating its effectiveness through rankings, the paper applies this model to evaluate and select medical providers for New York-based patients, showcasing its practicality and computational process. The findings from this comprehensive evaluation framework offer a structured approach for decision-making, enabling stakeholders to select medicine providers tailored to meet specific priorities or demands, ensuring timely and reliable access to critical medical supplies, especially in emergency situations.*

1. INTRODUCTION

Currently, numerous scholars are directing their attention toward issues within medical services, particularly in societies focused on service provision. The challenges within this domain, such as information gaps between patients and doctors, inflated pharmaceutical costs, and instances of unnecessary treatment, often lead to patient dissatisfaction. Consequently, recent research efforts have delved into diverse aspects of medical services, encompassing evaluations of hospital services, analyses of pharmaceutical pricing dynamics, explorations of personalized medicine's facets, and more. Surprisingly, amidst these investigations, the critical element of medicine supply within the medical supply chain has been neglected. However, the selection of appropriate medicine providers holds the potential to reduce medication costs and enhance patient contentment. This oversight becomes especially critical given the increasing frequency of natural disasters and diverse viral outbreaks, amplifying the significance of medicine supply in emergency care. Hence, the challenge of identifying suitable medicine providers remains unresolved. As the market demand for medical drugs continues to rise, the logistics involved in medicine distribution has gained substantial importance, ensuring the seamless flow of these essential products. Policies encouraging express delivery firms to enter the medical market, coupled with significant investments in logistics infrastructure, have prompted a growing number of pharmaceutical companies to opt for specialized third-party logistics (3PL) providers. This strategic move allows these companies to delegate the transportation and distribution of pharmaceutical goods to experts, enabling them to concentrate on enhancing their core competitive edge. The impact of choosing specific providers is termed the "provider selection effect." This effect signifies the variation in expenses attributed to including or excluding different providers in a network. For instance, a managed care organization might opt for providers known for less intense treatment methods while avoiding those known for highly intensive ones. The alteration in future expenditures due to selecting low or high-intensity providers

represents the provider selection effect concerning utilization. Likewise, the difference in rates among providers before negotiation defines the provider selection effect regarding pricing. Essentially, this effect gauges how selecting provider types influences subsequent expenses, distinct from tracking changes in rates or utilization patterns at a particular provider over time. Subsequent to provider selection, managed care organizations may pursue expenditure reductions by negotiating prices and implementing utilization management strategies. The alterations in reimbursement rates for a specific provider over time constitute the "bargaining effect," while changes in utilization over time represent the "utilization management effect." The bargaining effect refers to the price alterations, often reductions, resulting from negotiations with managed care organizations for inclusion in their network. Our industry analysis emphasizes that bargaining primarily focuses on price adjustments, significantly impacting expenditure changes. Managed care organizations typically secure price concessions by leveraging the ability to exclude providers from their network. When negotiating lower rates than previously charged, bargaining over prices leads to expenditure reduction, assuming all else remains constant. Distinguishing itself from the provider selection effect concerning price, the bargaining effect brings about rate changes for providers winning a contract, whereas provider selection assesses rate differences between network providers and others before negotiations commence, establishing new rates. Selecting a third-party cold chain medical logistics provider involves several factors and experts, making it a multiple criteria decision-making (MCDM) problem. Multiple criteria group decision-making involves assessing a range of alternatives against conflicting criteria, based on evaluations by multiple experts. Within MCDM, crucial aspects involve how to measure and rank these criteria. Evaluation information in MCDM usually comes in quantitative or qualitative forms. Linguistic terms have been favored for expressing qualitative variables due to their alignment with human thought processes. However, single linguistic terms often struggle to precisely capture people's cognitive assessments. Hence, to align more closely with human cognition, various extensions have emerged, such as the 2-tuple linguistic set, hesitant fuzzy linguistic term set, probabilistic linguistic term set, and continuous interval-valued linguistic term set. These extensions utilize membership, probability, or interval to represent uncertainty in decision-making. However, they fail to completely eradicate the influence of alternatives on experts' cognition. Rough sets, known for handling imprecise and uncertain data through lower and upper approximations of a target set, offer a valuable approach [7]. To address this issue, we leverage rough sets in conjunction with linguistic terms. Among these approaches, COPRAS stands out as a widely adopted method in multi-criteria decision-making. It operates by simultaneously maximizing the "group utility of the majority" and minimizing the "individual regret of the opponent" [11], making it effective for ranking and sorting a set of alternatives.

2. METHOD AND MATERIALS

As a response to the limitations of single linguistic terms in accurately reflecting people's cognitive assessments, various extensions have been introduced to better align with human cognition. Examples include the 2-tuple linguistic set, hesitant fuzzy linguistic term set, probabilistic linguistic term set, and continuous interval-valued linguistic term set. These extensions incorporate membership, probability, or intervals to capture uncertainty in decision-making. Despite these advancements, these approaches still grapple with the influence of alternatives on expert cognition. To address this challenge, rough sets, which provide lower and upper approximations of a target set, serve as an effective tool for handling imprecise, vague, and uncertain data. This approach is leveraged in combination with linguistic terms. Among these methods, COPRAS stands out as widely employed in multi-criteria decision-making, excelling in ranking and sorting alternatives. COPRAS is grounded in maximizing the "group utility of the majority" and minimizing the "individual regret of the opponent" simultaneously.

COPRAS method

In this segment, a practical example is detailed to demonstrate the implementation of the COPRAS method. The objective is to choose a specific count of medicine providers from a set of alternatives. A city in China is experiencing a rapid rise in the number of people infected with an unknown bird flu virus, necessitating urgent access to medicines for treating and curing those affected. Among five medical companies capable of supplying these medicines, the task is to select three providers to fulfill the city's urgent need. The criteria for evaluating these medicine providers have been identified based on relevant literature sources [12-14].

TABLE 1. Criteria

Delivery reliability	C1
Medicines quality	C2
Manufacturing capability	C3
Technical skills	C4
Medicines characteristics	C5
Lead time	C6
Unit price	C7

This table 1 proposed seven criteria which are described as follows.

- **Delivery Reliability (C1):** This criterion evaluates the reliability and consistency of medicine providers in delivering their products. It centers on the stability and predictability of their supply chain, guaranteeing a continuous and uninterrupted availability of medicines.
- **Medicines Quality (C2):** This criterion quantifies the proportion of medicines supplied by providers that meet or surpass the quality standards anticipated by consumers or those in need. High-quality medicines are deemed safe, effective, and compliant with regulatory mandates.
- **Manufacturing Capability (C3):** This criterion assesses a provider's capability to produce a defined quantity or volume of medicines within set timelines. It gauges their production efficiency and their ability to promptly meet demand.
- **Unit Price (C4):** This criterion denotes the price per unit of medicine offered by the provider. It encompasses the provider's pricing strategy, seeking a balance between affordability, quality maintenance, and reliability.
- **Technical Skills (C5):** This criterion pertains to the provider's technological proficiency in the manufacturing of medicines, encompassing the use of advanced techniques, equipment, and methods throughout the production process.
- **Medicines Characteristics (C6):** This criterion covers the distinct functionalities, features, or specialized attributes of the medicines offered. It assesses whether these medicines meet particular consumer or demander requirements or desired functionalities.
- **Lead Time (C7):** This criterion evaluates the time taken from ordering medicines to their actual delivery. It gauges the efficiency and promptness of the provider's supply chain and logistics in swiftly fulfilling orders.

3. RESULT AND DISCUSSION

TABLE 2. Evaluation information on medicine providers provided by medical experts

Medicine Provider	C1	C2	C3	C4	C5	C6	C7
A1	2.289	3.198	1.632	4.25	2.132	1.96	2.176
A2	2	3.808	5	2.61	3.024	2	1.632
A3	0.544	2.665	4	6	3.132	2.65	1.066
A4	1.044	3.264	3.198	2.72	5.325	2.176	2.132
A5	1.57	5.45	1.088	3.264	3.198	2.784	3

The numerical values in Table 2 depict evaluations of different medicine providers across multiple criteria. For example, considering A3, it performs exceptionally well in certain aspects like manufacturing capability (C3) and unit price (C4), scoring notably high at 4 and 6, respectively. This suggests a strong ability to produce medicines in quantity and offer competitive pricing. However, it falls short in delivery reliability (C1) and lead time (C7), scoring lower at 0.544 and 1.066, indicating potential weaknesses in consistency and order-to-delivery timing. Conversely, A2 showcases strengths in medicines quality (C2) and technical skills (C5) with scores of 3.808 and 3.024, respectively, but it holds average scores across other criteria and notably lacks in delivery reliability (C1). These assessments provide a comprehensive overview of each provider's strengths and weaknesses across critical aspects, facilitating decision-making when selecting a medicine provider based on specific priorities or requirements.

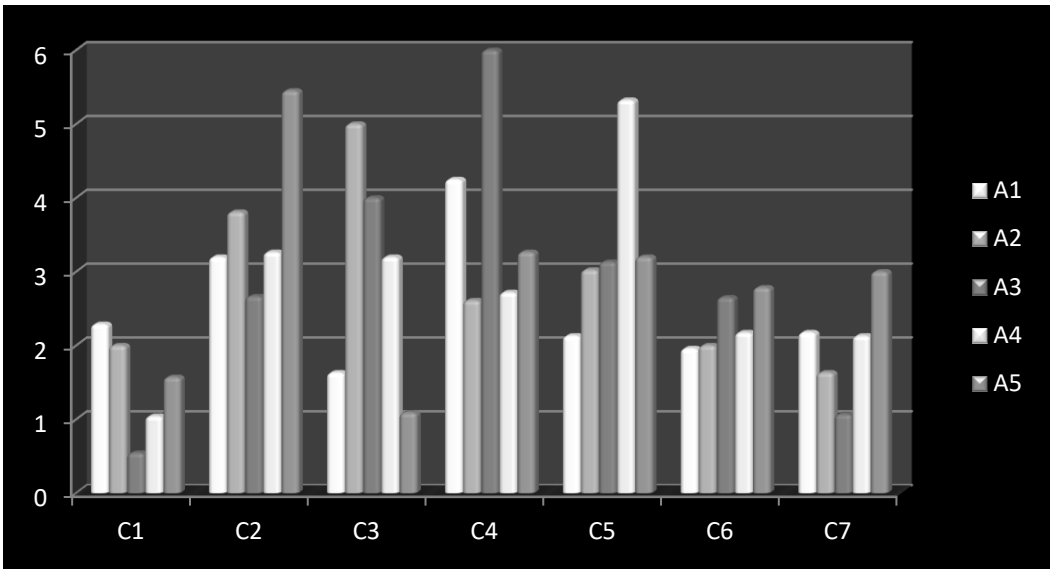


FIGURE 1. Evaluation information on medicine providers provided by medical experts

Figure 1 shows that the evaluation information provided by medical experts offers a comprehensive view of multiple medicine providers, each assessed across various criteria. Provider A1 demonstrated a range of scores from 1.632 to 4.25, showing an overall average evaluation of approximately 2.507. Meanwhile, Provider A2 exhibited a wider range, scoring between 1.632 and 5 across criteria, averaging around 2.926. Provider A3 showcased a broad spectrum, with scores varying from 0.544 to 6, resulting in an average evaluation of roughly 2.827. A4's scores fluctuated between 1.044 and 5.325, culminating in an average of approximately 2.896. Lastly, Provider A5 displayed scores ranging from 1.088 to 5.45, yielding an average evaluation of about 2.913. These values illuminate the diverse performance levels among the medicine providers, indicating their standing as assessed by medical experts across multiple evaluated criteria.

TABLE 3. Normalized Data

	C1	C2	C3	C4	C5	C6	C7
A1	0.3074	0.1739	0.1094	0.2255	0.1268	0.1694	0.2175
A2	0.2686	0.2071	0.3352	0.1385	0.1799	0.1729	0.1631
A3	0.0730	0.1450	0.2681	0.3184	0.1863	0.2290	0.1065
A4	0.1402	0.1775	0.2144	0.1443	0.3168	0.1881	0.2131
A5	0.2108	0.2964	0.0729	0.1732	0.1902	0.2406	0.2998

Table 3 showcases normalized data for each criterion across various medicine providers (A1 to A5). Normalization standardizes values within a consistent range (often between 0 and 1), facilitating comparisons of providers' performance across criteria. For instance, examining provider A3, it demonstrates relatively weak performance in delivery reliability (C1) with a normalized value of 0.073, highlighting deficiencies in this aspect compared to other providers. However, it excels in manufacturing capability (C3) and unit price (C4) with values of 0.268 and 0.318, respectively, indicating strength in these areas compared to its performance across other criteria. Meanwhile, provider A5 stands out in medicines quality (C2) and technical skills (C5) with normalized scores of 0.296 and 0.190, suggesting superior performance in these specific criteria compared to other providers. These normalized values enable a more straightforward comparison of each provider's relative strengths and weaknesses across evaluation criteria, aiding decision-makers in selecting the most suitable medicine provider based on specific priorities or preferences.

TABLE 4. Weight

	C1	C2	C3	C4	C5	C6	C7
A1	0.16	0.18	0.13	0.12	0.17	0.16	0.1
A2	0.16	0.18	0.13	0.12	0.17	0.16	0.1
A3	0.16	0.18	0.13	0.12	0.17	0.16	0.1
A4	0.16	0.18	0.13	0.12	0.17	0.16	0.1
A5	0.16	0.18	0.13	0.12	0.17	0.16	0.1

It seems that each criterion (C1 to C7) is assigned the same weight across all medicine providers (A1 to A5) in Table 4. These weights likely represent the relative importance or priority assigned to each criterion in the decision-making process for all providers. For example, if we consider the weight assigned to C2 (Medicines Quality), which is 0.18 for all providers, it indicates that across the board, decision-makers have deemed medicines quality as relatively more important compared to other criteria in evaluating medicine providers. Similarly, the consistent weights across all criteria for each provider suggest that in this evaluation, each criterion is given an equal level of importance or priority when assessing and comparing these providers. This equal weighting approach assumes that all criteria contribute equally to the overall evaluation or decision-making process.

TABLE 5. Weighted normalized decision matrix

	C1	C2	C3	C4	C5	C6	C7
A1	0.05	0.03	0.01	0.03	0.02	0.03	0.02
A2	0.04	0.04	0.04	0.02	0.03	0.03	0.02
A3	0.01	0.03	0.03	0.04	0.03	0.04	0.01
A4	0.02	0.03	0.03	0.02	0.05	0.03	0.02
A5	0.03	0.05	0.01	0.02	0.03	0.04	0.03

Table 5 displays the weighted normalized decision matrix, derived from combining the normalized data in Table 3 with the assigned weights from Table 4. Each cell in this matrix results from multiplying the normalized value from Table 3 by the corresponding weight from Table 4. This multiplication generates a weighted score for each criterion concerning each medicine provider, indicating the relative significance of each criterion for each provider. For instance, the value of 0.05 for Provider A1 and criterion C1 arises from multiplying the normalized score (0.3074 from Table 3) by its assigned weight (0.16 from Table 4). This matrix aids in quantifying the significance of each criterion for each provider by integrating both the normalized data and the assigned weights. These weighted scores serve as a basis for further analysis, facilitating the ranking or prioritization of medicine providers based on their performance across the evaluated criteria.

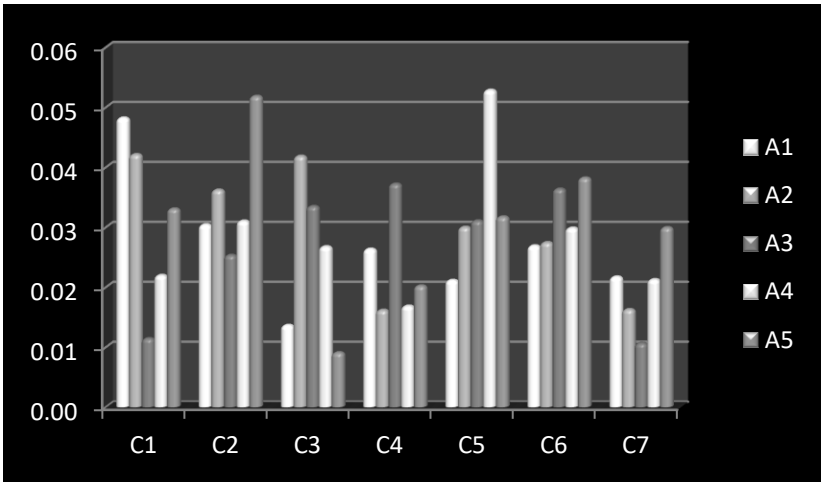


FIGURE 2. Weighted normalized decision matrix

Figure 2 shows across the criteria, Entity A1 displays varying normalized scores ranging from 0.01 to 0.05, while Entity A2 showcases scores ranging from 0.02 to 0.04. Entity A3 presents scores ranging from 0.01 to 0.04, Entity A4 from 0.02 to 0.05, and Entity A5 from 0.01 to 0.05. These values likely reflect the relative performance or

evaluation of each entity across the different criteria, considering the previously assigned weights to these criteria. The higher values suggest stronger performance or a better evaluation in the corresponding criteria compared to lower values within the matrix.

TABLE 6. Bi, Ci, and Min (Ci)/Ci

	Bi	**Ci**	**Min(Ci)/Ci**
Medicine Provider 1	0.140	0.049	0.8996
Medicine Provider 2	0.167	0.044	1.0000
Medicine Provider 3	0.139	0.047	0.9304
Medicine Provider 4	0.150	0.051	0.8552
Medicine Provider 5	0.146	0.068	0.6418

Table 6 displays three primary columns—Bi, Ci, and Min (Ci)/Ci—pertaining to five medicine providers. The Bi values, representing certain measurements or parameters, range from 0.140 to 0.146 for Providers 1 through 5, respectively. In the Ci column, values vary from 0.044 to 0.068 across the same providers. The Min (Ci)/Ci column showcases computed ratios, ranging from 0.8996 to 1.0000 for Providers 1 through 5. These ratios potentially illustrate the relationship between a minimum value derived from Ci and Ci itself. They offer insights into the relative influence or importance of Bi concerning Ci for each provider. Higher values in the Min (Ci)/Ci column may indicate a stronger connection between these parameters for specific medicine providers, suggesting a potentially more influential or significant impact of Bi concerning Ci for those particular entities.

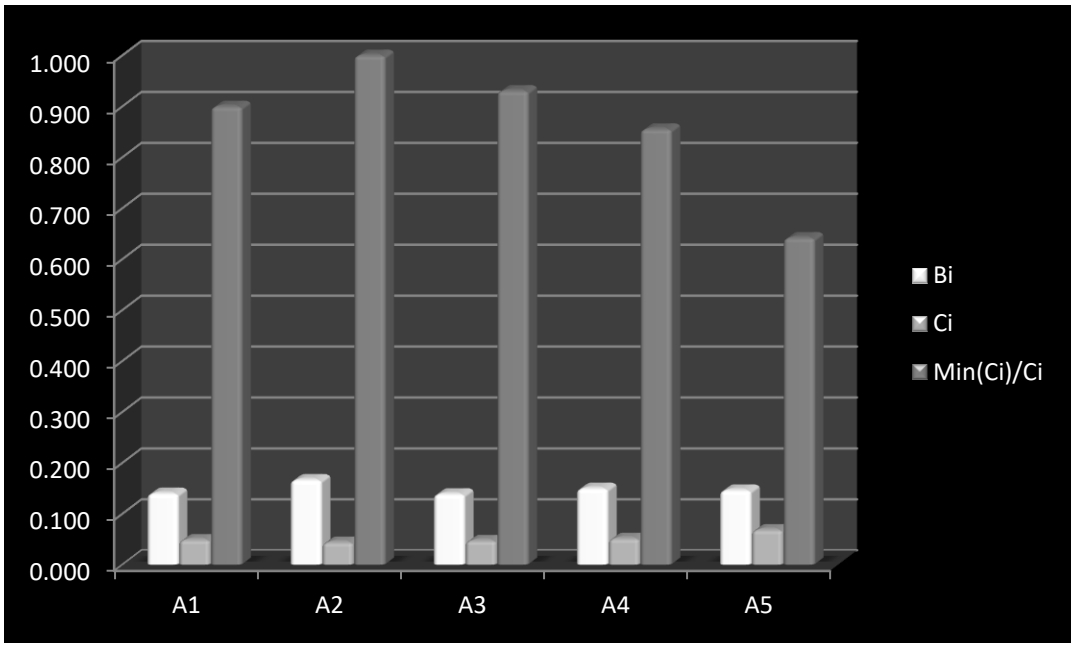


FIGURE 3. Bi, Ci, and Min (Ci)/Ci

In figure 3, the columns Bi, Ci, and Min(Ci)/Ci correspond to five distinct medicine providers. For Medicine Providers 1 through 5, the Bi values stand at 0.140, 0.167, 0.139, 0.150, and 0.146, respectively. The Ci values for the same providers are 0.049, 0.044, 0.047, 0.051, and 0.068. The Min(Ci)/Ci column showcases ratios ranging from 0.6418 to 1.0000, indicating the relationship between the minimum derived value from Ci against Ci itself for each provider. These values suggest varying degrees of influence or significance of Bi concerning Ci across the different medicine providers. A higher Min(Ci)/Ci ratio implies a more pronounced effect or importance of Bi compared to Ci for that specific provider, shedding light on the distinct relationships between these parameters for each entity.

TABLE 7. Qi and Ui

	Qi	**Ui**
Medicine Provider 1	0.194	85.5916
Medicine Provider 2	0.226	100.0000
Medicine Provider 3	0.194	85.8665
Medicine Provider 4	0.201	88.7113
Medicine Provider 5	0.185	81.5077

Table 7 presents two columns—Qi and Ui—pertaining to five medicine providers. The Qi values range from 0.185 to 0.226 for Providers 1 through 5, while the Ui values vary from 81.5077 to 100.0000 across the same providers. The Qi column likely represents specific quantitative metrics or scores assigned to each provider, showcasing their performance against certain criteria. Meanwhile, the Ui column likely denotes a different set of metrics associated with the providers, indicating another aspect of their evaluation or performance. These values offer a comparative view of the medicine providers' performance across the Qi and Ui metrics, reflecting their varying levels of achievement or measurement against these specific criteria or assessments.

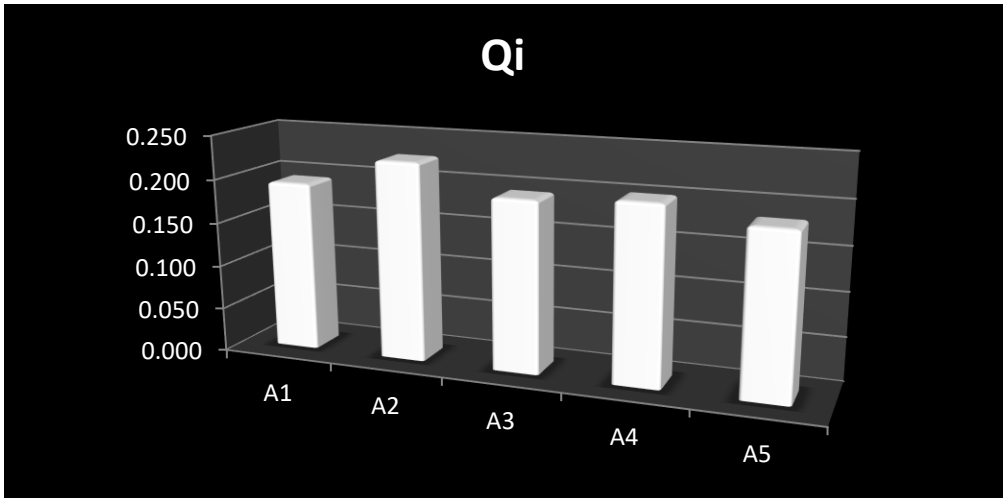


FIGURE 4. Qi values

The figure 4 provided Qi values for Medicine Providers 1 through 5 are as follows: Provider 1 has a Qi value of 0.194, Provider 2 has 0.226, Provider 3 has 0.194, Provider 4 has 0.201, and Provider 5 has 0.185. These Qi values likely represent specific measurements or scores associated with the performance, capability, or assessment of each medicine provider across certain criteria or evaluations. The differences in these Qi values may indicate varying levels of performance or effectiveness among the providers concerning the measured criteria or metrics.

TABLE 8. Rank

Medicine Provider	**Rank**
Medicine Provider 1	**4**
Medicine Provider 2	**1**
Medicine Provider 3	**3**
Medicine Provider 4	**2**
Medicine Provider 5	**5**

Table 8 displays the ranks assigned to five distinct medicine providers based on specific evaluation criteria, with rankings ranging from 1 to 5. Medicine Provider 2 attains the highest rank (1), implying its potentially superior performance or standing compared to the other providers. Conversely, Medicine Provider 5 holds the lowest rank (5), indicating a comparatively less favorable position or performance within this evaluation context. These rankings

establish a clear hierarchy, delineating each provider's position relative to the assessed criteria, offering insights into their varying performance levels.

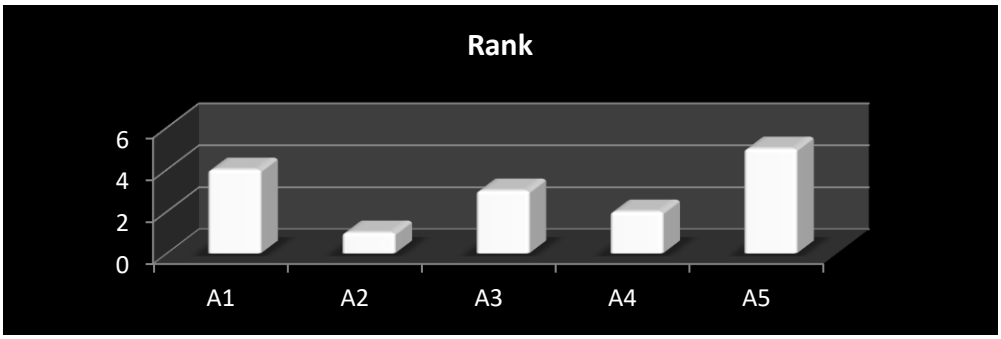


FIGURE 5. Ranking

Figure 5 shows that Provider 2 holds the highest rank (1), indicating it is likely considered the top performer or holds the most favorable position compared to the other providers. Conversely, Provider 5 holds the lowest rank (5), suggesting it might be considered the least favorable among the group based on the evaluation criteria used to assign these ranks.

4. CONCLUSION

In conclusion, the selection of medicine providers involves a comprehensive evaluation process across various criteria such as reliability, quality, pricing, production capacity, technological expertise, unique attributes of medicines, and delivery efficiency. Methods like COPRAS assist in decision-making by integrating normalized data, weighted scores, and comparative metrics to rank and prioritize providers based on their performance across these critical criteria. The tables presented in the assessment offer a systematic breakdown of each provider's strengths and weaknesses, aiding decision-makers in selecting the most suitable medicine providers tailored to specific priorities or requirements, especially crucial during urgent situations like responding to health crises or pandemics. This systematic evaluation framework enables a thorough understanding of provider capabilities, facilitating informed decisions to ensure timely and reliable access to essential medical supplies.

REFERENCES

[1]. Han, Xueliang, and Xi Chen. "A D-VIKOR method for medicine provider selection." In 2014 Seventh international joint conference on computational sciences and optimization, pp. 419-423. IEEE, 2014.

[2]. Hsu, John, Julie Schmittdiel, Edward Krupat, Terry Stein, David Thom, Bruce Fireman, and Joe Selby. "Patient choice: a randomized controlled trial of provider selection." Journal of general internal medicine 18, no. 5 (2003): 319-325.

[3]. Dandasi, Varun Venkatesh, Suresh Deepak Gurubasannavar, and Raghavendra Sunku. "ENHANCING SMART GRID SECURITY: A MULTI-CRITERIA EVALUATION THROUGH GRA METHOD." Management 14, no. 2: 153-167.

[4]. Dohmen, Peter JG, and Erik M. van Raaij. "A new approach to preferred provider selection in health care." Health Policy 123, no. 3 (2019): 300-305.

[5]. Suresh Deepak Gurubasannavar, “Performance Optimization for Micro-Frontend-Based Applications: A Predictive Analysis Using XG Boost Regression”, Journal of Business Intelligence and Data Analytics, 2(3), 2025, 1-7.

[6]. Mustare, Narendra B., Brijesh Singh, M. Vijaya Sekhar, Dhiraj Kapila, and Ajay Singh Yadav. "Iot and Big Data Analytics Platform to Analyze the Faults in the Automated Manufacturing Process Unit." In 2023 International Conference on New Frontiers in Communication, Automation, Management and Security (ICCAMS), vol. 1, pp. 1-6. IEEE, 2023.

[7]. Liao, Huchang, Jiaying Chang, Zhiying Zhang, Xiang Zhou, and Abdullah Al-Barakati. "Third-party cold chain medicine logistics provider selection by a rough set-based gained and lost dominance score method." International Journal of Fuzzy Systems 22 (2020): 2055-2069.

[8]. Chou, Shuo-Yan, F. Yu Vincent, Anindhita Dewabharata, and Luu Quoc Dat. "A fuzzy TOPSIS approach for medical provider selection and evaluation." In 2012 International conference on Fuzzy Theory and Its Applications (iFUZZY2012), pp. 322-326. IEEE, 2012.
[9]. Mustare, Narendra B. "Modified CNN Model for Malaria Diagnosis." Journal of Positive School Psychology 6, no. 3 (2022).
[10]. Tu, Lei, Yaqiong Lv, Yajie Zhang, and Xiaohua Cao. "Logistics service provider selection decision making for healthcare industry based on a novel weighted density-based hierarchical clustering." Advanced Engineering Informatics 48 (2021): 101301.
[11]. Newgard, Craig D., N. Clay Mann, Renee Y. Hsia, Eileen M. Bulger, O. John Ma, Kristan Staudenmayer, Jason S. Haukoos, Ritu Sahni, Nathan Kuppermann, and Western Emergency Services Translational Research Network (WESTRN) Investigators. "Patient choice in the selection of hospitals by 9-1-1 emergency medical services providers in trauma systems." Academic Emergency Medicine 20, no. 9 (2013): 911-919.
[12]. Tu, Lei, Yaqiong Lv, Yajie Zhang, and Xiaohua Cao. "Logistics service provider selection decision making for healthcare industry based on a novel weighted density-based hierarchical clustering." Advanced Engineering Informatics 48 (2021): 101301.
[13]. Wu, Jiayi, Yan Zhao, Chinmay Chakraborty, Sandeep Kumar Thota, Jingmin Xin, and Keping Yu. "Cell-Level Free Cervical Lesion Detection in Cytology Images Via Weakly Supervised Self-Correction." IEEE Journal of Biomedical and Health Informatics (2025).
[14]. Newhouse, Joseph P. "Reimbursing health plans and health providers: efficiency in production versus selection." Journal of economic literature 34, no. 3 (1996): 1236-1263.
[15]. Lindrooth, Richard C., Edward C. Norton, and Barbara Dickey. "Provider selection, bargaining, and utilization management in managed care." Economic Inquiry 40, no. 3 (2002): 348-365.
[16]. Chang, Jiaying, Huchang Liao, and Zhiying Zhang. "Third-party cold chain medicine logistic Provider selection by a rough set-based gained and lost dominance score method." In 2019 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 3287-3292. IEEE, 2019.
[17]. Sandeep Kumar Thota, Polavarapu Ashok, Mohammad El Yabroudi, Gummadi Hari, Suresh, Babu, Chennupati Narendra, Guduri Manisha, "A Novel Framework on Cardiovascular Disease Prediction Using Transfer Learning Technique", Trends in Sustainable Computing and Machine Intelligence, (2025), 86-98.
[18]. Mustare, Dr Narendra. "A Logical Approach of Data Mining Technique for the Prediction of Cardiovascular Disease." International Journal of Research and Analytical Reviews (IJRAR) UGC Approved-Journal 43602 (2019): 2348-1269.
[19]. Sahama, Tony, Andrew Stranieri, Kerryn Butler-Henderson, and Isaac Golden. "Medical system choice: Information that affects the selection of healthcare provider in Australia?." In Building Continents of Knowledge in Oceans of Data: The Future of Co-Created eHealth, pp. 596-600. IOS Press, 2018.
[20]. Herland, Matthew, Richard A. Bauder, and Taghi M. Khoshgoftaar. "Medical provider specialty predictions for the detection of anomalous medicare insurance claims." In 2017 IEEE international conference on information reuse and integration (IRI), pp. 579-588. IEEE, 2017.
[21]. Sunku, Raghavendra. "Beyond digitalization strategic automation as a driver of policy administration performance using linear and random forest regression." International Journal of Computer Science and Data Engineering 2, no. 4 (2025): 260.
[22]. Bozic, Kevin J., David Kaufman, Vanessa C. Chan, Stephanie Caminiti, and Courtland Lewis. "Factors that influence provider selection for elective total joint arthroplasty." Clinical Orthopaedics and Related Research® 471 (2013): 1865-1872.
[23]. Bhanderi, Jaydeep, Jitendra Mehta, and Kinjal Rank. "A Parametric Study of Simple Footing and Piled Raft." INTERNATIONAL JOURNAL OF ENGINEERING DEVELOPMENT AND RESEARCH 3, no. 4 (2015): 820-826.
[24]. Sunku, Raghavendra. "Data Intelligence for Workforce Management: Machine Learning Models for Payroll and Resource Optimization." International Journal of Artificial intelligence and Machine Learning 3, no. 3 (2025): 1-7.
[25]. Rademakers, Jany, Jessica Nijman, Anne EM Brabers, Judith D. de Jong, and Michelle Hendriks. "The relative effect of health literacy and patient activation on provider choice in the Netherlands." Health policy 114, no. 2-3 (2014): 200-206.
[26]. Stargardt, Tom, and Sotiris Vandoros. "Pharmaceutical pricing and reimbursement regulation in Europe." In Encyclopedia of health economics, pp. 29-36. Elsevier, 2014.
[27]. Redekop, W. Ken, and Deirdre Mladsi. "The faces of personalized medicine: a framework for understanding its meaning and scope." Value in Health 16, no. 6 (2013): S4-S9.
[28]. Lam, Ka-Chi, Ran Tao, and Mike Chun-Kit Lam. "A material supplier selection model for property developers using fuzzy principal component analysis." Automation in Construction 19, no. 5 (2010): 608-618.
[29]. Tracey, Michael, and Chong Leng Tan. "Empirical analysis of supplier selection and involvement, customer satisfaction, and firm performance." Supply chain management: An international journal 6, no. 4 (2001): 174-188.

[30]. Chang, Tsung-Han. "Fuzzy VIKOR method: A case study of the hospital service evaluation in Taiwan." Information Sciences 271 (2014): 196-212.
[31]. KINJAL RANK, "Comparative Study on Effect of Expansive Soil Properties While Using Stabilizer as Lime Fly ashAnd Cement Dust Manufacturing Waste", Journal of Emerging Technologies and Innovative Research", 3(6), 2019.
[32]. Zavadskas, Edmundas Kazimieras, Artiras Kaklauskas, Friedel Peldschus, and Zenonas Turskis. "Multi-attribute assessment of road design solutions by using the COPRAS method." The Baltic journal of Road and Bridge engineering 2, no. 4 (2007): 195-203.
[33]. Dandasi, Varun Venkatesh, Suresh Deepak Gurubasannavar, and Raghavendra Sunku. "ENHANCING SMART GRID SECURITY: A MULTI-CRITERIA EVALUATION THROUGH GRA METHOD." Management 14, no. 2: 153-167.
[34]. Organ, Arzu, and Engin Yalçın. "Performance evaluation of research assistants by COPRAS method." European Scientific Journal 12, no. 10 (2016): 102-109.
[35]. Turanoglu Bekar, Ebru, Mehmet Cakmakci, and Cengiz Kahraman. "Fuzzy COPRAS method for performance measurement in total productive maintenance: a comparative analysis." Journal of Business Economics and Management 17, no. 5 (2016): 663-684.
[36]. Aka, Venkata Pavan Kumar, and Kiran Kumar Mandula Samuel. "Adoption of SAP FSCM–Enhancing Collections and Dispute Processes in Spain, Portugal, and UK Operations." International Journal of Information Technology and Management Information Systems (IJITMIS) 15, no. 2 (2024): 148-161.
[37]. George, Diana, and Sam G. Benjamin. "Survey Paper on Different Types Of Prediction Algorithm For Air Quality Index And Comparative Study On Types Of Algorithms Used." INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS 9, no. 6 (2021): b557-b562.
[38]. Aka, V. P. K. "Enhancing SAP Full-Cycle Automation and Cost Efficiency with OpenText VIM: A Regression-Based Predictive Study." International Journal of Cloud Computing and Supply Chain Management 1, no. 3 (2025).
[39]. Hezer, Seda, Emel Gelmez, and Eren Özceylan. "Comparative analysis of TOPSIS, VIKOR and COPRAS methods for the COVID-19 Regional Safety Assessment." Journal of infection and public health 14, no. 6 (2021): 775-786.
[40]. Kumari, Reetu, and Arunodaya Raj Mishra. "Multi-criteria COPRAS method based on parametric measures for intuitionistic fuzzy sets: application of green supplier selection." Iranian journal of science and technology, Transactions of Electrical Engineering 44, no. 4 (2020): 1645-1662.
[41]. Amoozad Mahdiraji, Hannan, Sepas Arzaghi, Gintaras Stauskis, and Edmundas Kazimieras Zavadskas. "A hybrid fuzzy BWM-COPRAS method for analyzing key factors of sustainable architecture." Sustainability 10, no. 5 (2018): 1626.
[42]. Aka, Venkata Pavan Kumar, and Kiran Kumar Mandula Samuel. "Predictive Modeling for Brownfield Migration from SAP ECC 6.0 to S4HANA A Machine Learning Approach for Effort Evaluation Under the SAP Rise Program." International Journal of Computer Engineering and Technology (IJCET) 14, no. 1 (2023): 232-248
[43]. Diana George, R. Navya, Vinitha V, "Next-Gen Air Quality Index Forecasting with Hybrid Machine Learning Models and Cloud Synergy", International Journal of Engineering Trends and Technology, 73(8), 2025, 129-136.
[44]. Aka, V. P. K. "Enterprise SAP Tax Machine Migration: Using Machine Learning and Architecture Best Practices for Vertex 9 Transformation." Journal of Artificial Intelligence and Machine Learning 2, no. 3 (2024): 1-7.
[45]. Dandasi, V. V. "Application of ARAS Methodology in Supply Chain Performance Evaluation." International Journal of Cloud Computing and Supply Chain Management 1, no. 2 (2025): 1-7.
[46]. Kundakcı, Nilsen, and A. Işık. "Integration of MACBETH and COPRAS methods to select air compressor for a textile company." Decision Science Letters 5, no. 3 (2016): 381-394.
[47]. Popovic, Gabrijela, Dragisa Stanujkic, and Sanja Stojanovic. "Investment project selection by applying COPRAS method and imprecise data." Serbian Journal of Management 7, no. 2 (2012): 257-269.
[48]. Thota, Sandeep Kumar, Kumari Gubbala, Ashok Polavarapu, Vikram Narayandas, Hari Suresh Babu Gummadi, Narendra Chennupati, Sreedhar Babu Seshagani, Shivakrishna Deepak Veeravalli, and Manisha Guduri. "Adversarial Training with Attention-Guided DCGAN for Robust Lung Segmentation in Medical Imaging." In 2025 IEEE Region 10 Symposium (TENSYMP), pp. 1-6. IEEE, 2025.
[49]. Dandasi, Varun Venkatesh, Suresh Deepak Gurubasannavar, and Raghavendra Sunku. "ENHANCING SMART GRID SECURITY: A MULTI-CRITERIA EVALUATION THROUGH GRA METHOD." Management 14, no. 2: 153-167.