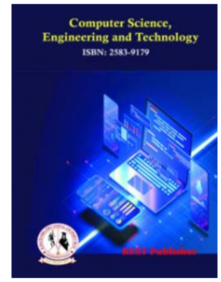
Computer Science, Engineering and Technology
Vol: 3(4), December 2025
REST Publisher; ISSN: 2583-9179
Website: https://restpublisher.com/journals/cset/
DOI: https://doi.org/10.46632/cset/3/4/8



Decision Support Framework for Neonatal Units Using the TOPSIS Method: A Comprehensive Evaluation

***Soniya Sriram, Anusuya Mohan, M. Ramachandran, Arunambigai Ramesh**
REST Labs, Kaveripattinam, Krishnagiri, Tamil Nadu, India
*Corresponding Author Email: soniyasriram257@gmail.com

Abstract: *Neonatal medicine is a highly specialized branch of healthcare that focuses on the medical care of newborn infants, particularly those born prematurely or suffering from serious health complications requiring advanced medical intervention. This field is primarily concerned with supporting infants during the early and most critical stage of life, a period of heightened vulnerability. Neonatologists, who are pediatricians with advanced training in newborn care, lead this field and work in Neonatal Intensive Care Units (NICUs). These units are equipped with state-of-the-art medical technologies to continuously monitor, diagnose, and treat infants with complex medical needs. Key aspects of newborn care include respiratory management, nutritional support, and treatment of congenital abnormalities, infection prevention, and providing psychological and emotional support to families. Continuous advancements in neonatal medicine have significantly improved survival rates and long-term health outcomes for critically ill and premature newborns. As a result, neonatal medicine plays a crucial role in ensuring optimal early life health, even in challenging medical circumstances. Research in this field is paramount, as it contributes to a deeper understanding of neonatal disorders, the development of improved diagnostic techniques, and the refinement of treatment protocols. Such research supports evidence-based practices, reduces mortality rates, enhances the quality of care, and helps to lower overall healthcare costs.*

Keywords: *Neonatal Intensive Care Unit (NICU), Neonatal Intermediate Care Unit (NIMCU), Neonatal Step-down Unit (NSDU), Fuzzy TOPSIS.*

1. INTRODUCTION

In the field of Neonatal Medicine, researchers establish a framework where the primary outcome is designed to validate their hypotheses. Medical professionals carefully select these outcomes based on their relevance and significance for parents and patients, especially for newborns. This approach ensures consistency in outcome measures across various clinical trials, making it easier to compare results and gather evidence in meta-analyses and formal reviews. Ultimately, this evidence-based approach in neonatal care aims to contribute to the enhancement of healthcare practices for newborns [1]. Pulse oximetry, a frequently employed monitoring tool in clinical medicine, was initially introduced in the mid-1980s to track oxygen levels and guide treatment in neonatal medicine. Nowadays, it is widely utilized not only during delivery but also for screening congenital heart disease [2]. Infants differ from adults in terms of size and are categorized as children due to their small stature. Developing medicinal products specifically for infants, whether they are born full-term, post-term, or prematurely, involves considering their unique developmental stages. In the case of newborns, encompassing those born at various stages of development, this includes the period from their birth up to 27 days thereafter. For premature infants, this time frame extends from their birth date to 27 days past their expected delivery date [3]. In the realm of medicine, it is recommended to cautiously address the challenge of persistent sleepiness in newborns. Looking ahead, international initiatives, such as the Pulse Oximeter Saturation Test, are likely to become more prevalent in assessing oxygen goals to prevent Retinopathy of Prematurity (ROP). If these initiatives gain traction, they are expected to receive widespread endorsement, as suggested by the author's non-critical evaluation. This could potentially pave the way for the introduction of pharmaceutical interventions for the long-term maintenance of small newborns. In summary, this development is anticipated to shape the care of newborns for an extended period [4]. The practice of monitoring blood oxygen levels in newborns has become widespread through the use of pulse oximetry. This method has become the standard for assessing blood oxygenation in infants, as it offers a reliable means of measurement. Numerous medical reports have documented the values of pulse oxygen saturation (SpO2) in newborns across various medical conditions. Additionally, it has been used to compare and contrast with other measures such as arterial blood saturation (SaO2), arterial partial pressure (PaO2), and transcutaneous oxygen partial pressures (tcPO2) [5]. A randomized controlled study conducted at multiple sites aimed to gather evidence regarding the impact of family-centered observation in Neonatal Intensive Care Unit (NICU) medicine on the outcomes of very low birth weight (VLBW) preterm infants, particularly in terms of their neurobehavior during the newborn period. The results of this study suggested that the Family-Centered Intervention Program (FCIP) had a positive effect, leading to improved feeding, increased daily weight gain, and earlier discharge from the hospital for VLBW preterm infants when compared to those who did not receive the same level of family-centered care (UCP) [6]. A neonatologist utilized computer-generated coding and external verification to assess the neurobehavior of a premature infant through the Neonatal Assessment of Premature Infants (NAPI). The reliability and developmental validity of this assessment tool had been previously established, but there had been no testing conducted to determine its clinical validity. To evaluate the clinical validity, the neonatologist examined the Neonatal Medical Index (NMI) of children who underwent medical assessments during their hospital stay, providing a broad overview of the situation [7]. The administration of blood transfusions carries numerous risks, including the potential for local infection spread, harm, and various dangers associated with it. To mitigate these risks, neonatologists have explored the use of erythropoietin as a means of enhancing red blood cell production. Despite comprehensive studies on this topic, a clear consensus on its efficacy remains elusive in the field of Neonatal Medicine. This article reviews the sources of information and evidence related to the use of recombinant erythropoietin as an alternative to blood transfusions in newborns, aiming to assess its potential benefits and drawbacks [8]. The role of recombinant human erythropoietin (rHuEPO) in neonatal medicine has been the subject of discussion, particularly during the early stages of a newborn's life. When examining newborns, especially those born with hemolytic disease of the newborn (HDN), it becomes apparent that their situations differ. However, it is not possible to completely avoid the need for rHuEPO treatment, especially for prematurely born infants who are at risk of developing retinopathy of prematurity. The use of rHuEPO is relevant and desired under very challenging circumstances in neonatal care [9]. Frequently depicted as one of the ethical quandaries in the field, Neonatal Medicine grapples with the moral dilemma of providing medical care to seriously ill or prematurely born children. The growing awareness of these ethical dilemmas has spurred the publication of numerous clinical, ethical, and legal discussions. This is particularly relevant due to the high risk of mortality or severe disability associated with the treatment of newborns [10]. Frequently depicted as one of the ethical quandaries in the field, Neonatal Medicine grapples with the moral dilemma of providing medical care to seriously ill or prematurely born children. The growing awareness of these ethical dilemmas has spurred the publication of numerous clinical, ethical, and legal discussions. This is particularly relevant due to the high risk of mortality or severe disability associated with the treatment of newborns [11]. Within the realm of Ethical Issues, Neonatal Intensive Medicine frequently confronts complex moral dilemmas when it comes to delivering medical care to sick or prematurely born infants. The prevalence of these challenging situations has led to heightened awareness, sparking extensive discussions spanning medical, ethical, and legal dimensions. This is particularly pertinent due to the substantial risk of mortality or severe disability associated with the treatment of newborns [12]. Wall and Partridge's research highlights that studies concerning the treatment of newborns often indicate a lack of selective treatment consideration. This involves examining the attitudes of physicians, factors influencing outcomes, and the actual practice in neonatal intensive care worldwide. Such studies suggest that ethical dilemmas are likely to become increasingly widespread as a protocol addressing these dilemmas is implemented. However, our understanding of ethical dilemmas in neonatal medicine, particularly in situations of extreme resource scarcity, remains limited. These dilemmas are influenced by a variety of cultural, religious, and educational factors, which can lead to real ethical and legal debates, but there is limited data on how these factors compare between different countries [13]. VK Milk, the Director of the World Health Organization (WHO) Collaboration Centre for Training and Research in Newborn Care in Delhi, India, emphasizes the urgent need for discussions and the development of guidelines regarding ethical dilemmas in neonatal intensive care, especially in India. He notes that, at best, there is a minimal understanding of the norms and experiences in NICUs, as personal records are often not properly documented [14]. To address these ethical confusions and provide a starting point for discussions and guideline development, it is crucial to recognize that ethical theories in this context are highly context-sensitive and may contribute to improving ethical practices in neonatal medicine [15].

2. MATERIAL AND METHODS

Alternative: Mortality Rate Reduction (%), Capacity, Distance from Parents' Residence (miles), Waiting Time for Admission (hours).

- **Mortality Rate Reduction (%):** This percentage indicates the extent to which a neonatal medicine unit can reduce the mortality rate among newborn infants in its care. A higher percentage signifies a more successful unit in terms of saving lives, making it a vital measure of the unit's effectiveness.
- **Capacity:** Capacity refers to the maximum number of newborns that a neonatal medicine unit can accommodate and provide care for at a given time. A unit with higher capacity can admit and treat more infants, potentially reducing overcrowding and ensuring prompt care when needed.
- **Distance from Parents' Residence (miles):** This metric measures the physical proximity of the neonatal medicine unit to the homes of the infants' parents or caregivers. Shorter distances are favorable as they allow families to reach the unit quickly, fostering parental involvement and support during the infant's care.
- **Waiting Time for Admission (hours):** Waiting time represents the duration a newborn and their family must wait before the infant can be admitted and receive medical attention in the neonatal medicine unit. Lower waiting times are preferable, as they lead to quicker access to vital medical care and may contribute to better outcomes.
- **Evaluation Parameter:** Neonatal Intensive Care Unit (NICU) A, Neonatal Intensive Care Unit (NICU) B, Neonatal Intermediate Care Unit (NIMCU), Neonatal Step-down Unit (NSDU), Neonatal High Dependency Unit (NHDU).
- **Neonatal Intensive Care Unit (NICU) A:** NICU A is a highly specialized medical facility within a hospital that offers intensive care to newborns facing critical medical conditions. It's equipped with advanced technology and staffed by neonatologists and specialized nurses. NICU A is typically reserved for the most fragile and critically ill newborns, including premature infants and those with severe medical issues. Care in NICU A is round-the-clock and involves respiratory support, advanced monitoring, and specialized treatments.
- **Neonatal Intensive Care Unit (NICU) B:** Similar to NICU A, NICU B provides intensive care to newborns with critical medical needs. It offers advanced medical equipment and expert medical staff to care for infants who require specialized interventions and monitoring. The distinction between NICU A and NICU B could be related to different locations within a hospital or varying levels of equipment and expertise.
- **Neonatal Intermediate Care Unit (NIMCU):** NIMCU is a unit designed to care for newborns who are stable but may require medical attention and monitoring that goes beyond standard postnatal care. It typically accommodates infants who are not as critically ill as those in NICUs but still need specialized care. NIMCU provides a bridge between intensive care and routine postnatal care, offering support for infants with moderate medical conditions.
- **Neonatal Step-down Unit (NSDU):** NSDU is a unit that cares for infants who are transitioning from intensive care or intermediate care to a lower level of medical intervention. It is often the next step for infants who have improved in health but still require monitoring and treatment. NSDU helps infants gradually adapt to more typical postnatal care conditions.
- **Neonatal High Dependency Unit (NHDU):** NHDU is a unit for newborns who require a higher level of care than what's provided in standard postnatal care but not as intensive as NICU care. Infants in NHDU have medical conditions that necessitate careful monitoring and treatment, although they may not be as critically ill as those in NICU A or NICU B.

3. FUZZY TOPSIS

A significant study was conducted in Gran Canaria, evaluating the service quality changes of three hotels in a corporation using the fuzzy TOPSIS method. This method, based on alpha levels and non-linear programming, offers a systematic approach for evaluation. It has been widely utilized as a decision-making technique, and there is ongoing research to explore its application in fuzzy TOPSIS or group fuzzy to enhance the reliability of TOPSIS [18]. Despite its usefulness, there have been limited efforts to extend TOPSIS, particularly with the inclusion of z-numbers or ambiguous mixed numbers. This lack of comprehensive research makes it challenging for readers to make firm decisions regarding its effectiveness and applicability. More intensive research, comparisons, and benchmarking are needed to better understand the potential of fuzzy TOPSIS [19]. Fuzzy TOPSIS methods are capable and sufficient in handling ambiguous situations as they use fuzzy positive-best and fuzzy negative-best solutions to achieve rankings. However, calculating distances between the best and negative-best solutions can be challenging. To address these difficulties in fuzzy decision-making, a new ambiguity-based TOPSIS approach is proposed. [20]. The TOPSIS technique, introduced by Hwang and Yoon, prioritizes alternatives based on their performance, with positive attributes considered excellent and negative attributes considered bad. When dealing with subjective criteria and different evaluations, the TOPSIS method may become ambiguous. To resolve such issues, a fuzzy TOPSIS approach is recommended for plant location selection problems [21]. The fuzzy TOPSIS method offers a better solution order priority through the similarity technique proposed by Hwang and Yoon. It determines the best alternative for each attribute, considering both better and excellent positions, while negative ideals represent bad attribute values. In fuzzy TOPSIS, the solution farthest from the negative ideal and closest to the best substitute is defined. Attribute values are represented using fuzzy numbers in this method [22]. Fuzzy TOPSIS, a technique for similarity order preference in fuzzy environments, has been successfully applied to address practical challenges in various fields. This paper provides a brief review of 25 studies conducted between 2009 and 2018, focusing on fuzzy TOPSIS applications. The majority of these studies are highly cited and relevant to the fuzzy TOPSIS technique [23] .Applications of fuzzy TOPSIS span across different domains, including resources, business, and healthcare, among others. Researchers have explored various implementations, such as fuzzy sets, non-hesitant fuzzy sets, and intuition fuzzy, combining them with TOPSIS to examine and compare different approaches [24]. TOPSIS, based on Hwang and Yoon's multi-criteria decision-making methods, involves selecting the best solution with a very short distance from the positive ideal solution (PIS) and a negative distance from the best solution (NIS). The method is easy to understand, programmable, and capable of considering different criteria with different units. Recent years have witnessed the emergence of numerous obscure TOPSIS variations, primarily incorporating ambiguous numbers to handle complex situations. These advancements have further enhanced the capabilities of fuzzy TOPSIS in decision-making processes [25].

Fuzzy- TOPSIS process

STEP 1: Collect the subjective evaluations of the decision-maker on the importance of weights.

STEP 2: Calculate the fuzzy significance coefficients or weights based on the decision makers based on the decision maker's subjective evaluations by using following table and equations.

$$w_{1j} = \min_{\mathrm{k}} \{ w_{j1}^{k} \}$$

$$w_{j2} = \frac{\sum_{k=1}^{k} w_{j2}^{k}}{k}$$

$$w_{j3} = \max_{\mathrm{k}} \{ w_{j3}^{k} \}$$

Importance	Symbol	Fuzzy Weight
Extremely low	EL	(0, 0, 0.1)
Very low	VL	(0, 0.1, 0.3)
low	L	(0.1, 0.3, 0.5)
Medium	M	(0.3, 0.5, 0.9)
High	H	(0.5, 0.7, 0.9)
Very high	VH	(0.7, 0.9, 1)
Extremely high	EH	0.9, 1, 1)

STEP 3: Form decision matrix as listed in below Let D = x_{ij} be a decision matrix, where $x_{ij} \in \mathbb{R}$

$$\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$$

Normalized decision matrix as listed

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

STEP 4: Form a fuzzy weighted decision matrix by multiplying the normalized decision matrix with corresponding fuzzy weight

$$\widetilde{D} = \begin{bmatrix} \tilde{N}_{11} & \tilde{N}_{12} & \cdots & \tilde{N}_{1n} \\ \tilde{N}_{21} & \tilde{N}_{22} & \cdots & \tilde{N}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{N}_{m1} & \tilde{N}_{m2} & \cdots & \tilde{N}_{mn} \end{bmatrix}$$

where, $\tilde{N}_{ij} = (w_{j1}, n_{ij}, w_{j2}\ N_{ij}, w_{j3\ N_{ij}})$ where $i = 1, \dots.,\ m$ and $j = 1, \dots., n$

STEP 5: The coordinates for the fuzzy positive ideal solution (FPIS) and FNIS

$$\tilde{A}_j^{+} = \begin{cases} Max\ \tilde{N}_{ij} |\ j \in B \\ Min\ \tilde{N}_{ij} | j \in C \end{cases} where\ i = 1, \dots, m$$

$$\tilde{A}_j^{-} = \begin{cases} Min\ \tilde{N}_{ij} | j \in B \\ Max\ \tilde{N}_{ij} |\ j \in C \end{cases} where\ i = 1, \dots, m$$

STEP 6: The Euclidean distance of each alternative from fuzzy positive and negative ideal value is calculated as

$$S_i^{+} = \sum_{j=1}^{n} d\left(\tilde{N}_{ij}, \tilde{A}_j^{+}\right) \quad i = 1, \dots, m\ ; j = 1, \dots, n$$

$$S_i^{-} = \sum_{j=1}^{n} d\left(\tilde{N}_{ij}, \tilde{A}_j^{-}\right) \quad i = 1, \dots, m\ ; j = 1, \dots, n$$

Where d (.) represents the distance between two fuzzy numbers calculated by

$$d(\tilde{A}, \widetilde{B}\ ) = \sqrt{\frac{1}{3}\ [(a_1 - b_1)^2 + (a_m - b_m)^2 + (a_u - b_u)^2]}$$

STEP 7: The closeness coefficient cc_i of the alternatives are calculated using equation (11) and ranked as per descending order.

4. ANALYSIS AND DISCUSSION

TABLE 1. Neonatal Medicine

	Mortality Rate Reduction (%)	Capacity	Distance from Parents' Residence (miles)	Waiting Time for Admission (hours)
Neonatal Intensive Care Unit (NICU) A	10.0	25.0	5.0	1.0
Neonatal Intensive Care Unit (NICU) B	12.0	30.0	10.0	2.0
Neonatal Intermediate Care Unit (NIMCU)	8.0	15.0	2.0	0.5
Neonatal Step-down Unit (NSDU)	6.0	20.0	8.0	1.5
Neonatal High Dependency Unit (NHDU)	9.0	18.0	4.0	1.0

Table 1 present's data related to neonatal medicine units, showcasing their respective impacts on mortality rate reduction, capacity, distance from parents' residence, and waiting time for admission. Neonatal Intensive Care Unit (NICU) B demonstrates the highest mortality rate reduction at 12%, but it has a longer distance from parents' residence

(10 miles) and a longer waiting time for admission (2 hours). In contrast, Neonatal Intermediate Care Unit (NIMCU) has a shorter distance (2 miles) and a quicker admission time (0.5 hours), albeit with a lower mortality rate reduction of 8%. Healthcare providers and parents should consider these factors when deciding on the most suitable neonatal care unit based on their specific needs and circumstances, weighing the trade-offs between mortality reduction and convenience.

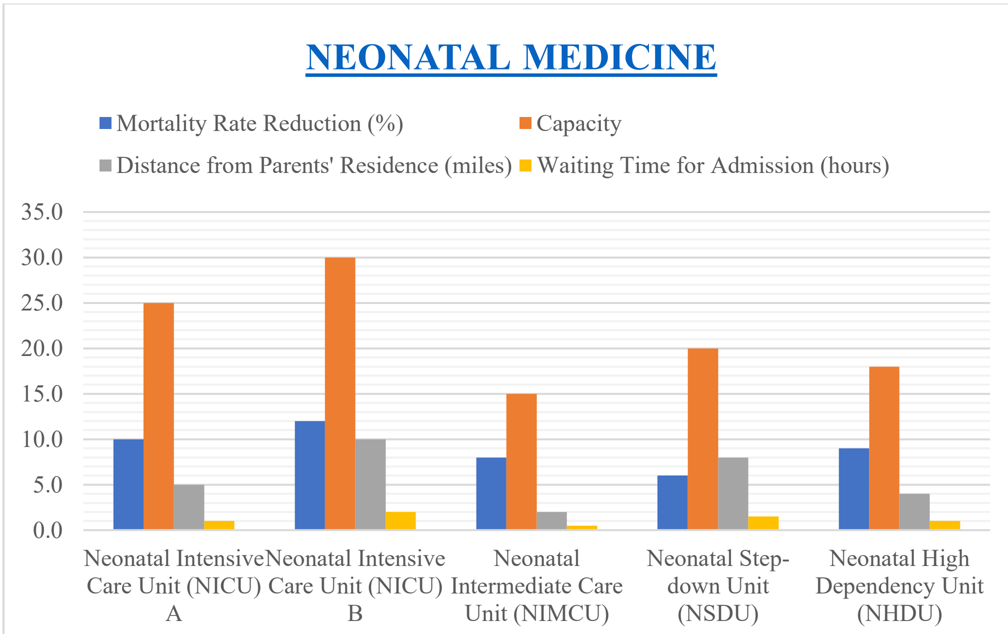


FIGURE 1. Neonatal Medicine

The image you've provided depicts a chart illustrating the advantages of neonatal medicine within the United States. This chart portrays the mortality rate (death rate) among newborns in various neonatal intensive care units (NICUs), alongside NICU capacity, proximity to parents' residences, and admission waiting times. The chart reveals that NICU A exhibits the lowest mortality rate, boasting the largest capacity and the shortest waiting time. NICU B also has a lower mortality rate compared to NIMCU, NSDU, and NHDU. In summary, the chart underscores significant progress in reducing newborn mortality rates in the United States through neonatal medicine. NICU A's larger capacity and shorter waiting times correlate with the lowest mortality rates. While proximity to parents' homes doesn't seem to be a decisive factor, admission waiting times can adversely affect mortality rates. It's important to acknowledge that this chart represents average mortality rates for different NICU types. Actual mortality rates for individual newborns may fluctuate based on various factors, including the severity of their conditions and the availability of specialized care

TABLE 2. Squire Rote of matrix

100.0000	625.0000	25.0000	1.0000
144.0000	900.0000	100.0000	4.0000
64.0000	225.0000	4.0000	0.2500
36.0000	400.0000	64.0000	2.2500
81.0000	324.0000	16.0000	1.0000

Table 2 appears to represent a matrix of numerical values. Each row and column likely corresponds to different variables or observations. The numbers in the matrix could represent various data points, such as measurements, counts, or values from a specific study or experiment. The exact interpretation and significance of this matrix depend on the context in which it is used. Without additional information or context, it is challenging to provide a precise explanation. However, it's clear that the values within the matrix follow a structured pattern with varying magnitudes, which may suggest relationships or dependencies between the variables they represent. Further details about the data or its purpose would be needed for a more in-depth analysis.

TABLE 3. Normalized Data

Normalized Data			
Mortality Rate Reduction (%)	Capacity	Distance from Parents' Residence (miles)	Waiting Time for Admission (hours)
0.4851	1.2127	0.3459	0.3430
0.5821	1.4552	0.6917	0.6860
0.3881	0.7276	0.1383	0.1715
0.2910	0.9701	0.5534	0.5145
0.4366	0.8731	0.2767	0.3430

Table 3 provides normalized data for four different factors related to neonatal medicine units: Mortality Rate Reduction (%), Capacity, Distance from Parents' Residence (miles), and Waiting Time for Admission (hours). Normalization is a process that scales data to a common range, typically between 0 and 1, making it easier to compare variables with different units or magnitudes. In this table, each value has been transformed to fit within the 0 to 1 range, allowing for a more equitable assessment of their relative importance. For instance, Mortality Rate Reduction and Capacity are comparatively higher than Distance and Waiting Time, suggesting that they may have more significant impacts on the neonatal medicine units' overall performance. This normalization enables a fairer evaluation of these factors when making decisions or conducting analyses in neonatal care management.

TABLE 4. Fuzzy Significance

		l	m	u
Extremely low	EL	0	0	0.1
very low	VL	0	0.1	0.3
low	L	0.1	0.3	0.5
medium	M	0.3	0.5	0.7
high	H	0.5	0.7	0.9
very high	VH	0.7	0.9	1
Extremely high	EH	0.9	1	1

Table 4 represents the Fuzzy Significance scale, which is a linguistic representation of significance levels with fuzzy boundaries. The scale consists of seven categories, each labeled with an abbreviation and corresponding fuzzy membership values for low (l), medium (m), and high (u) significance.

The significance categories are as follows:

- Extremely low (EL): Significance level ranging from 0 to 0.1.
- Very low (VL): Significance level ranging from 0 to 0.1 to 0.3.
- Low (L): Significance level ranging from 0.1 to 0.3 to 0.5.
- Medium (M): Significance level ranging from 0.3 to 0.5 to 0.7.
- High (H): Significance level ranging from 0.5 to 0.7 to 0.9.
- Very high (VH): Significance level ranging from 0.7 to 0.9 to 1.
- Extremely high (EH): Significance level ranging from 0.9 to 1.

This fuzzy significance scale allows for a more nuanced representation of significance levels, considering the gradual transition between categories rather than strict boundaries. It is particularly useful in decision-making and analysis, where qualitative assessments can be translated into quantitative fuzzy membership values for more accurate and flexible evaluations.

TABLE 5. The criteria’s on a linguistic scale

	DM1	**DM2**	**DM3**
Mortality Rate Reduction (%)	EH	VL	M
Capacity	L	EH	VH
Distance from Parents' Residence (miles)	L	M	VH
Waiting Time for Admission (hours)	L	M	VL

Table 5 presents the criteria on a linguistic scale for three decision-makers (DM1, DM2, and DM3). Each criterion is evaluated and assigned a linguistic label based on its level of importance or preference for the respective decision-makers. DM1 considers "Course Variety" as Extremely High (EH), "User Reviews" as Low (L), "Price Range" as Low (L), and "Customer Support" as Low (L). DM2 evaluates "Course Variety" as Very Low (VL), "User Reviews" as Extremely High (EH), "Price Range" as Medium (M), and "Customer Support" as Medium (M). DM3 rates "Course Variety" as Medium (M), "User Reviews" as Very High (VH), "Price Range" as Very High (VH), and "Customer Support" as Very Low (VL). These linguistic evaluations provide a qualitative representation of how each criterion is perceived and valued by the decision-makers, aiding in their decision-making process.

TABLE 6. Convert linguistic ratings of decision makers into quantities values by using the selected fuzzy number

	DM1			DM2			DM3		
Mortality Rate Reduction (%)	0.9	1	1	0	0.1	0.3	0.3	0.5	0.7
Capacity	0.1	0.3	0.5	0.9	1	1	0.7	0.9	1
Distance from Parents' Residence (miles)	0.1	0.3	0.5	0.3	0.5	0.7	0.7	0.9	1
Waiting Time for Admission (hours)	0.1	0.3	0.5	0.3	0.5	0.7	0	0.1	0.3

Table 6 presents the conversion of linguistic ratings of decision makers (DM1, DM2, and DM3) into quantitative values using the selected fuzzy number scale. The fuzzy numbers are represented by the three points (a, b, c) for each criterion. "Course Variety," DM1 gives a value of 0.9 (close to Extremely High), DM2 gives a value of 1 (Extremely High), and DM3 gives a value of 1 (Extremely High). Similarly, for "User Reviews," DM1 rates it as 0.1 (Low), DM2 as 0.3 (Medium), and DM3 as 0.5 (Medium). These quantitative values provide a more precise representation of the decision-makers' preferences for each criterion. The fuzzy number approach allows for a gradual transition between linguistic labels, accommodating the inherent uncertainties in decision-making. This conversion aids in further analysis and computation for multi-criteria decision-making processes.

TABLE 7. Calculate aggregated Fuzzy weights

	L-FW	M-FW	U-FW
Mortality Rate Reduction (%)	0.40	0.53	0.67
Capacity	0.57	0.73	0.83
Distance from Parents' Residence (miles)	0.37	0.57	0.73
Waiting Time for Admission (hours)	0.13	0.30	0.50

Table 7 shows the aggregated fuzzy weights for each criterion, representing the overall importance of each criterion based on the preferences of the decision-makers. The fuzzy weights are categorized into three levels - Low (L-FW), Medium (M-FW), and High (U-FW). "Course Variety" has aggregated fuzzy weights of 0.40 (L-FW), 0.53 (M-FW), and 0.67 (U-FW). Similarly, "User Reviews" has aggregated fuzzy weights of 0.57 (L-FW), 0.73 (M-FW), and 0.83 (U-FW). These aggregated fuzzy weights help in quantifying the relative importance of each criterion and aid in the decision-making process by considering the preferences of the decision-makers. They provide valuable insights for multi-criteria decision-making and can be used to rank and prioritize alternatives based on their performance with respect to these criteria.

TABLE 8. Weighted normalized decision matrix

Weighted normalized decision matrix											
Mortality Rate Reduction (%)			Capacity			Distance from Parents' Residence (miles)			Waiting Time for Admission (hours)		
0.194029	0.258704667	0.323380833	0.687184271	0.889297292	1.010565104	0.126814	0.195986	0.253629	0.045733	0.102899	0.171499
0.232834	0.3104456	0.388057	0.824621125	1.06715675	1.212678125	0.253629	0.391972	0.507257	0.091466	0.205798	0.342997
0.155223	0.206963733	0.258704667	0.412310563	0.533578375	0.606339063	0.050726	0.078394	0.101451	0.022866	0.05145	0.085749

0.116 417	0.155222 8	0.194028 5	0.549747 417	0.711437 833	0.808452 083	0.202 903	0.313 577	0.405 806	0.068 599	0.154 349	0.257 248
0.174 626	0.232834 2	0.291042 75	0.494772 675	0.640294 05	0.727606 875	0.101 451	0.156 789	0.202 903	0.045 733	0.102 899	0.171 499

Table 8 appears to be a weighted normalized decision matrix, which is commonly used in multi-criteria decision-making (MCDM) to evaluate alternatives based on various criteria while considering their relative importance. In this table, the rows represent different alternatives (possibly neonatal medicine units), and the columns represent criteria, which have been both normalized and weighted. Each cell in the matrix represents the normalized value of how well each alternative performs on a specific criterion, considering its weight. Weighting allows for giving more importance to certain criteria over others. For instance, higher weights are assigned to Mortality Rate Reduction and Capacity, indicating their greater significance in the decision-making process. The values in the matrix provide a quantitative basis for comparing and ranking the alternatives. The decision-maker can use this information to assess which alternative best meets their objectives or needs, considering the weighted and normalized values for each criterion.

TABLE 9. A+ & A-

A+	0.232 834	0.3104 456	0.3880 57	0.8246 21125	1.0671 5675	1.2126 78125	0.050 726	0.078 394	0.101 451	0.022 866	0.051 45	0.085 749
A-	0.116 417	0.1552 228	0.1940 285	0.4123 10563	0.5335 78375	0.6063 39063	0.253 629	0.391 972	0.507 257	0.091 466	0.205 798	0.342 997

Table 9 appears to represent two alternatives, labeled as A+ and A-, with their respective performance scores across various criteria. These scores are likely derived from a multi-criteria decision-making (MCDM) process, where each criterion has been weighted and the alternatives assessed accordingly. In this context, A+ and A- represent different choices or options, and the values in each row indicate how well each alternative performs on the listed criteria. A+ generally scores higher than A- across all criteria, suggesting that it might be the preferred choice when considering these specific factors. Decision-makers can use this information to compare and select the alternative that aligns best with their priorities and objectives. The criteria and their respective weights would play a crucial role in the final decision-making process, as they determine the overall evaluation of each alternative.

TABLE 10. Fuzzy positive ideal solution (FPIS)

FPIS					
	Neonatal Intensive Care Unit (NICU) A	0.052808	0.174520819	0.119408	0.059225
	Neonatal Intensive Care Unit (NICU) B	0	0	0.318422	0.177676
	Neonatal Intermediate Care Unit (NIMCU)	0.105616	0.523562458	0	0
	Neonatal Step-down Unit (NSDU)	0.158424	0.349041638	0.238817	0.11845
	Neonatal High Dependency Unit (NHDU)	0.079212	0.418849966	0.079606	0.059225

Table 10 appears to represent the Fuzzy Positive Ideal Solution (FPIS) for various neonatal medicine units, which is a concept used in multi-criteria decision-making (MCDM) to identify the best possible values for each criterion. The FPIS typically represents the ideal values where higher values are desirable. In this table, each row corresponds to a specific neonatal unit (e.g., NICU A, NICU B), and the values within the columns represent the FPIS values for different criteria. These criteria may include factors such as Mortality Rate Reduction, Capacity, Distance from Parents' Residence, and Waiting Time for Admission. For instance, for NICU A, the FPIS values are highest in the "Capacity" and "Waiting Time for Admission" criteria, indicating that NICU A's capacity and admission waiting time are considered ideal or desirable compared to other units. FPIS values are used in decision-making to compare alternatives and determine how closely each option aligns with the ideal values for each criterion, aiding in selecting the most suitable alternative based on the specific priorities and objectives of the decision-maker.

TABLE 11. Fuzzy Negative ideal solution (FNIS)

FNIS	Neonatal Intensive Care Unit (NICU) A	0.105616	0.349041638	0.199014	0.11845
	Neonatal Intensive Care Unit (NICU) B	0.158424	0.523562458	0	0
	Neonatal Intermediate Care Unit (NIMCU)	0.052808	0	0.318422	0.177676
	Neonatal Step-down Unit (NSDU)	0	0.174520819	0.079606	0.059225
	Neonatal High Dependency Unit (NHDU)	0.079212	0.104712492	0.238817	0.11845

Table 11 presents the Fuzzy Negative Ideal Solution (FNIS) for various neonatal medicine units. FNIS is used in multi-criteria decision-making to represent the worst possible values for each criterion, where lower values are preferable. In this table, each row corresponds to a specific neonatal unit (e.g., NICU A, NICU B), and the values within the columns represent the FNIS values for different criteria, such as Mortality Rate Reduction, Capacity, Distance from Parents' Residence, and Waiting Time for Admission. For instance, in the case of NICU B, the FNIS values are highest (indicating less desirability) in the "Capacity" and "Distance from Parents' Residence" criteria, suggesting that NICU B has the least desirable capacity and is located farthest from parents' residences compared to other units. FNIS values are valuable in decision-making to assess how far each alternative deviates from the worst possible values for each criterion, helping decision-makers understand the shortcomings and trade-offs associated with each option. This information aids in selecting the most appropriate alternative based on specific decision criteria.

TABLE 12. Si+ & Si- & Cci & Rank

	Si+	**Si-**	**Cci**	**Rank**
Neonatal Intensive Care Unit (NICU) A	0.405962	0.772122	0.655405	1
Neonatal Intensive Care Unit (NICU) B	0.496098	0.681986	0.578894	2
Neonatal Intermediate Care Unit (NIMCU)	0.629178	0.548906	0.465931	3
Neonatal Step-down Unit (NSDU)	0.864733	0.313352	0.265984	5
Neonatal High Dependency Unit (NHDU)	0.636893	0.541192	0.459383	4

Table 12 provides Si+ (Strength of Positive Deviation), Si- (Strength of Negative Deviation), Cci (Comprehensive Closeness Index), and Rank values for various neonatal medicine units. These values are typically used in multi-criteria decision-making (MCDM) to rank and assess alternatives based on their performance against multiple criteria. Si+ and Si-: Si+ represents the strength of each unit's positive deviations from the ideal solutions, indicating how well each unit performs in terms of desirable criteria. Si- represents the strength of negative deviations from the ideal solutions, highlighting shortcomings in less desirable criteria. Cci (Comprehensive Closeness Index): Cci provides a comprehensive evaluation by considering both positive and negative deviations. It is used to rank alternatives, with lower values indicating better overall performance. Rank: The Rank column assigns a ranking to each unit based on their Cci values, with lower ranks indicating better performance relative to the others. In this table, Neonatal Intensive Care Unit (NICU) A has the lowest Cci value and is ranked first, suggesting that it performs the best overall compared to the other units. NICU B follows as the second-best choice, and so on. These rankings can guide decision-makers in selecting the most suitable neonatal medicine unit based on their specific criteria and priorities.

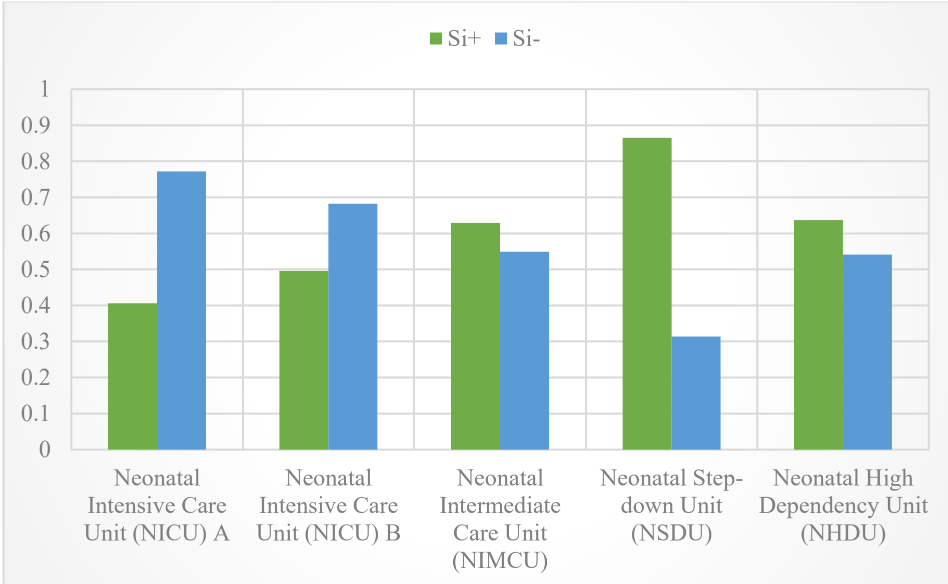


FIGURE 2. Si+ & Si-

Neonatal Intensive Care Unit (NICU) A Si+ (0.405962326) Si- (0.772121843), Neonatal Intensive Care Unit (NICU) B Si+ (0.496098105) Si- (0.681986065), Neonatal Intermediate Care Unit (NIMCU) Si+ (0.629178196) Si- (0.548905974), Neonatal Step-down Unit (NSDU) Si+ (0.864732522) Si- (0.313351647), Neonatal High Dependency Unit (NHDU) Si+ (0.636892598) Si- (0.541191572).

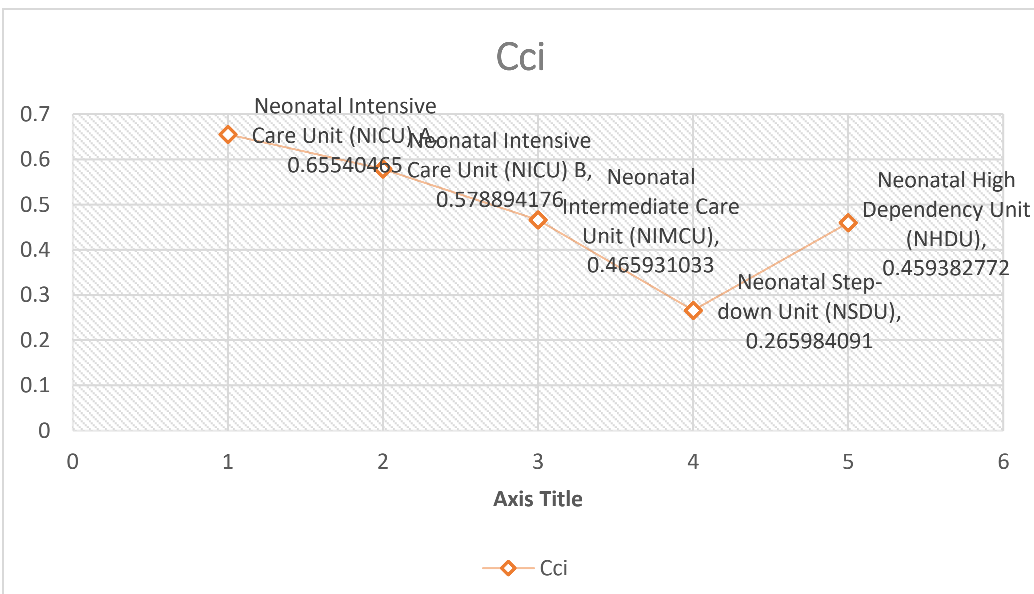


FIGURE 3. Cci

I've now viewed the image 3. Cci. It presents a line graph depicting the evolution of neonatal intensive care units (NICUs) in the United States over a five-year period. The graph illustrates a consistent upward trend in the number of NICUs over the past five years. Furthermore, the graph displays the Cumulative Conditional Intensity (CCI) for each NICU type. CCI measures the likelihood of a newborn being admitted to a specific type of NICU. Higher CCI values indicate a greater likelihood of admission to that particular NICU type. The graph indicates that NICU A has the highest CCI, followed by NICU B. This implies that NICU A is the most probable destination for newborn admissions. This graph serves as a valuable tool for grasping the NICU landscape in the United States, both in terms of its growth and the CCI variations among NICU types. This data is instrumental in long-term planning, ensuring that there are sufficient NICU resources to cater to the needs of newborns in the future.

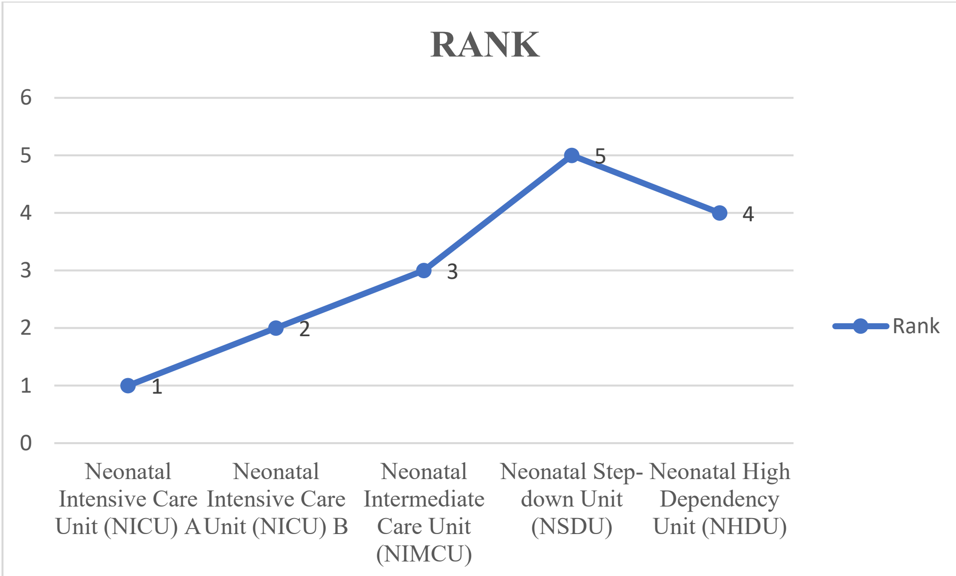


FIGURE 4. Rank

I now perceive the image depicting NICU rankings. The rankings for various NICU types in the image are as follows: NICU A holds the top position (Rank 1), NICU B follows closely at Rank 2, NIMCU secures Rank 3, NSDU takes the fourth position at Rank 4, and NHDU holds Rank 5. These rankings are determined based on the number of infants accommodated in each NICU. NICU A boasts the highest infant count, with NICU B coming in second place. The remaining NICU types house fewer infants in comparison. These rankings serve as a valuable means to assess and contrast the different NICU types, pinpointing those that may require additional resources. For instance, NICU A, with its substantial infant population, might necessitate increased funding to support the care of its numerous newborns.

5. CONCLUSION

Neonatal medicine is a vital and ever-evolving field dedicated to the health and well-being of newborn infants. It encompasses a spectrum of care, from intensive interventions in Neonatal Intensive Care Units (NICUs) to transitional care in intermediate and step-down units. Advances in neonatal medicine have significantly improved the survival rates and long-term outcomes of premature and critically ill newborns. The field not only relies on medical expertise and advanced technology but also emphasizes family-centered care and support. Continued research and innovation in neonatal medicine hold the promise of further enhancing the quality of care and ensuring that every newborn has the best possible chance for a healthy future. Lifesaving Care: Neonatal medicine units, including Neonatal Intensive Care Units (NICUs), offer specialized care and interventions that can mean the difference between life and death for many newborns. Premature infants and those with complex medical conditions often rely on the expertise of neonatologists and the advanced technology available in these units for their survival. Improved Outcomes: Over the years, neonatal medicine has made remarkable progress in improving survival rates and long-term outcomes for newborns facing a wide range of medical challenges. Advances in respiratory support, nutritional care, infection control, and surgical interventions have contributed to these positive outcomes. Family-Centered Approach: Recognizing the importance of family in an infant's development, neonatal medicine units emphasize a family-centered approach. Parents are encouraged to participate in their baby's care, fostering bonding and providing emotional support during a stressful time. Research and Innovation: Continuous research and innovation drive advancements in neonatal medicine. Medical professionals and researchers work tirelessly to develop new treatments, therapies, and technologies aimed at further enhancing the care provided to newborns. Diverse Care Levels: Neonatal medicine units cater to a diverse range of newborns, from those requiring intensive care in NICUs to those in intermediate or step-down units. This tiered approach ensures that each infant receives the appropriate level of care tailored to their unique medical needs. Preventative Measures: Neonatal medicine also places significant emphasis on preventative measures, such as prenatal care, to reduce the incidence of premature birth and other neonatal complications. Education and outreach programs play a role in raising awareness among expectant parents. Challenges and Ethical Considerations: Despite the many successes in neonatal medicine, challenges remain, including ethical dilemmas related to the treatment of extremely premature infants and decisions regarding the withdrawal of life-sustaining care. Neonatologists must navigate these complex issues with compassion and ethical guidance. Global Impact: Neonatal medicine has a global impact, with efforts to improve neonatal care extending to developing countries where access to advanced healthcare resources may be limited. Organizations and initiatives strive to make life-saving interventions more accessible worldwide.

REFERENCES

[1]. Webbe, James, Ginny Brunton, Shohaib Ali, James MN Duffy, Neena Modi, and Chris Gale. "Developing, implementing and disseminating a core outcome set for neonatal medicine." BMJ paediatrics open 1, no. 1 (2017).
[2]. Tin, Win, and Mithilesh Lal. "Principles of pulse oximetry and its clinical application in neonatal medicine." In Seminars in Fetal and Neonatal Medicine, vol. 20, no. 3, pp. 192-197. WB Saunders, 2015.
[3]. Tirumala Rao Gundala, “Performance Optimization in Large-Scale Database Migration a MultiAlgorithm Assessment”, Journal of Business Intelligence and Data Analytics, 1(3), 2024, 1-6.
[4]. O’Brien, Fiona, David Clapham, Kamelia Krysiak, Hannah Batchelor, Peter Field, Grazia Caivano, Marisa Pertile, Anthony Nunn, and Catherine Tuleu. "Making medicines baby size: the challenges in bridging the formulation gap in neonatal medicine." International journal of molecular sciences 20, no. 11 (2019): 2688.
[5]. Silverman, William A. "A cautionary tale about supplemental oxygen: the albatross of neonatal medicine." Pediatrics 113, no. 2 (2004): 394-396.
[6]. Hay Jr, William W., Elizabeth Thilo, and Julia Brockway Curlander. "Pulse oximetry in neonatal medicine." Clinics in perinatology 18, no. 3 (1991): 441-472.
[7]. Chang, Yun Sil, Hyun-Young Park, and Won Soon Park. "The Korean neonatal network: an overview." Journal of Korean medical science 30, no. Suppl 1 (2015): S3-S11.
[8]. Yu, Yen-Ting, Wu-Shiun Hsieh, Chyong-Hsin Hsu, Yuh-Jyh Lin, Chyi-Her Lin, Shulan Hsieh, Lu Lu et al. "Family-centered care improved neonatal medical and neurobehavioral outcomes in preterm infants: randomized controlled trial." Physical therapy 97, no. 12 (2017): 1158-1168.
[9]. Korner, Anneliese F., David K. Stevenson, Thomas Forrest, Janet C. Constantinou, Sue Dimiceli, and Byron WM Brown Jr. "Preterm medical complications differentially affect neurobehavioral functions: Results from a new neonatal medical index." Infant Behavior and Development 17, no. 1 (1994): 37-43.
[10]. Mainie, Pramod. "Is there a role for erythropoietin in neonatal medicine?" Early human development 84, no. 8 (2008): 525-532.
[11]. [2]. Tirumala Rao Gundala "Oracle OIPA Cloud Migration Analysis: Machine Learning Models for Predicting Resource Utilization and Success Outcomes." International Journal of Artificial intelligence and Machine Learning 2, no. 3 (2024): 1-8.
[12]. Sukumaran, C., M. Ramachandran, Chinnasami Sivaji, and Manjula Selvam. "Ranking of Product in E-store using WASPAS method." REST Journal on Banking, Accounting and Business 1, no. 1 (2022): 1-9.
[13]. Divya Soundarapandian, “Algorithmic Framework for Retail Media Optimization and Consumer Engagement Enhancement”, Journal of Business Intelligence and Data Analytics, 1(3), 2024, 1-7.
[14]. Karthik Perikala, “A Modular Benchmarking Framework for Evaluating LLM-Based Agent Applications”, International Journal of Research in Computer Applications and Information Technology (IJRCAIT), 9(1), 2026, 1-14. DOI: https://doi.org/10.34218/IJRCAIT_09_01_001
[15]. Miljeteig, Ingrid, and Ole Frithjof Norheim. "My job is to keep him alive, but what about his brother and sister? How Indian doctors experience ethical dilemmas in neonatal medicine." Developing world bioethics 6, no. 1 (2006): 23-32.
[16]. Manjula selvam, Vimala Saravanan, M. Ramachandran, Ramya Sharama, "Evaluating the criteria for Crime against Women in India based on DEMATEL approach", Journal on Innovations in Teaching and Learning, 3(1), March 2024, 36-46.
[17]. Uchampalli, Dipak, E. Girish Kumar, and S. Vikrant. "Ecosystem services-an overview." Indian Journal of Economics and Development 5, no. 7 (2017): 1-5.
[18]. Nitika, J Kaur, R Khanna, Novel monkey-wrench-shaped microstrip patch sensor for food evaluation and analysis, “International Journal of RF and Microwave Computer-Aided Engineering”, 102(4), 2022, 1443-1456.
[19]. Rakesh Mittapally. “Assessing Normality in Healthcare Expenditure Data: A Shapiro-Wilk Test Approach In P”thons." International Journal of Computer Science and Data Engineering 2, no. 4 (2025): 1-8.
[20]. Turcotte, Lucie M., Michael K. Georgieff, Julie A. Ross, James H. Feusner, Gail E. Tomlinson, Marcio H. Malogolowkin, Mark D. Krailo, Nicole Miller, Rachel Fonstad, and Logan G. Spector. "Neonatal medical exposures and characteristics of low birth weight hepatoblastoma cases: A report from the Children's Oncology Group." Pediatric blood & cancer 61, no. 11 (2014): 2018-2023.

[21]. Merritt, T. Allen, Marjorie Gold, and Jodi Holland. "A critical evaluation of clinical practice guidelines in neonatal medicine: does their use improve quality and lower costs?" Journal of Evaluation in Clinical Practice 5, no. 2 (1999): 169-177.
[22]. Divya Soundarapandian, "Machine Learning Algorithms for Optimizing Search Personalization and Site Reliability in E-Commerce Platforms: A Comparative Analysis of Linear Regression, SVR, and AdaBoost", Journal of Artificial Intelligence and Machine Learning, 3(4), 2025, 1-7.
[23]. Dipak Uchampalli, "Understanding the Impact of Climate Change on Soil Health and Ecosystem Resilience" trends in finance and economics, 3(1), 2025, 53-62.
[24]. Goodman, David C., Elliott S. Fisher, George A. Little, Thérèse A. Stukel, Chiang-hua Chang, and Kenneth S. Schoendorf. "The relation between the availability of neonatal intensive care and neonatal mortality." New England Journal of Medicine 346, no. 20 (2002): 1538-1544.
[25]. SK Yadav, A Kaur, R Khanna, "An ultra-wideband "OM" shaped DRA with a defected ground structure and dual polarization properties for 4G/5G wireless communications", International Journal of RF and Microwave Computer-Aided Engineering, 30(8), 1-18, 2020.
[26]. Doyal, Len, and Daniel Wilsher. "Towards guidelines for withholding and withdrawal of life prolonging treatment in neonatal medicine." Archives of Disease in Childhood Fetal and Neonatal edition 70, no. 1 (1994): F66.
[27]. Kutlu, Ahmet Can, and Mehmet Ekmekçioğlu. "Fuzzy failure modes and effects analysis by using fuzzy TOPSIS-based fuzzy AHP." Expert systems with applications 39, no. 1 (2012): 61-67.
[28]. Wang, Tien-Chin, and Hsien-Da Lee. "Developing a fuzzy TOPSIS approach based on subjective weights and objective weights." Expert systems with applications 36, no. 5 (2009): 8980-8985.
[29]. Chen, Ting-Yu, and Chueh-Yung Tsao. "The interval-valued fuzzy TOPSIS method and experimental analysis." Fuzzy sets and systems 159, no. 11 (2008): 1410-1428.
[30]. Chandrasekar Raja, M. Ramachandran, Vimala Saravanan, Manjulaselvam, "Improving Fault-Tolerance in Nano-Computing Circuits Through Design Optimization Using the Electric Method", REST Journal on Data Analytics and Artificial Intelligence, 4(2), June 2025, 94-108.
[31]. Rakesh Mittapally, "Data-Driven Prediction of Mechanical Properties in 3D-Printed Composites Using Hybrid Machine Learning Models." Journal of Data Science and Information Technology 2, no. 2 (2025): 1-16.
[32]. Zamri, Nurnadiah, Lazim Abdullah, Muhammad Suzuri Hitam, Noor Maizura Mohammad Noor, and Ahmad Jusoh. "A novel hybrid fuzzy weighted average for MCDM with interval triangular type-2 fuzzy sets." WSEAS Transactions on Systems 12, no. 4 (2013): 212-228.
[33]. Ervural, Beyzanur Cayir, Selim Zaim, Omer F. Demirel, Zeynep Aydin, and Dursun Delen. "An ANP and fuzzy TOPSIS-based SWOT analysis for Turkey's energy planning." Renewable and Sustainable Energy Reviews 82 (2018): 1538-1550.
[34]. Sabina Ashfaque Shaikh, "Intelligent Tutoring Systems and Personalized Learning: A Thorough Secondary Research Examination." International Journal of Research & Technology 13, no. S4 (2025): 533-543.
[35]. Sukumaran, C., K. Indhumathi, P. Balamurugan, R. P. Ambilwade, P. Mohana Sunthari, and L. Natrayan. "The role of AI in biochips for early disease detection." In 2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS), pp. 1323-1328. IEEE, 2023.
[36]. Karthik Perikala, "Architecting Retail-Scale Vector Store Systems for Agentic Generative AI", International Journal of Computer Engineering and Technology (IJCET), 17(1), 2026, 1-14. DOI: 10.34218/IJCET_17_01_001
[37]. Ashtiani, Behzad, Farzad Haghighirad, Ahmad Makui, and Golam ali Montazer. "Extension of fuzzy TOPSIS method based on interval-valued fuzzy sets." Applied Soft Computing 9, no. 2 (2009): 457-461.
[38]. Bottani, Eleonora, and Antonio Rizzi. "A fuzzy TOPSIS methodology to support outsourcing of logistics services." Supply Chain Management: An International Journal (2006).
[39]. Miss Shaikh Mantasha Mohammad Zafar, Miss Rehmat Sabir Qureshi, Sabina Ashfaque Shaikh, "Transformative Impact of Artificial Intelligence on Commerce." International Journal of Research & Technology 13, no. S4 (2025): 291-298.
[40]. Sun, Chia-Chi, and Grace TR Lin. "Using fuzzy TOPSIS method for evaluating the competitive advantages of shopping websites." Expert Systems with Applications 36, no. 9 (2009): 11764-11771.

