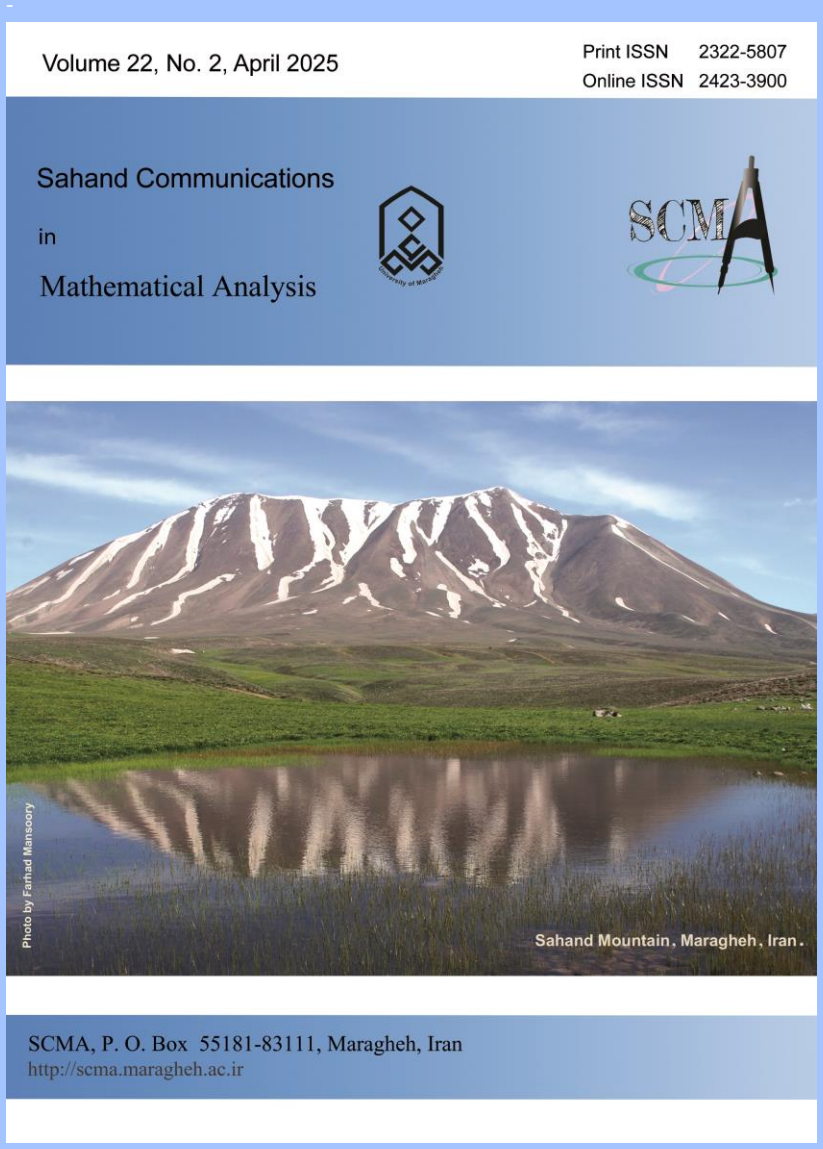
A Hybrid Decision Making Framework with Pythagorean Fuzzy Information for Childhood Cancer Prognosis

Naveen Kumar and Juthika Mahanta

Sahand Communications in Mathematical Analysis

Print ISSN: 2322-5807
Online ISSN: 2423-3900
Volume: 22
Number: 2
Pages: 109-141

Sahand Commun. Math. Anal.
DOI: 10.22130/scma.2024.2038238.1851



Sahand Communications in Mathematical Analysis (SCMA) Vol. 22 No. 2 (2025), 109-141
http://scma.maragheh.ac.ir
DOI: 10.22130/scma.2024.2038238.1851

A Hybrid Decision Making Framework with Pythagorean Fuzzy Information for Childhood Cancer Prognosis

Naveen Kumar[1] and Juthika Mahanta[2*]

Abstract. Medical information is complex and confidential, making accurate diagnosis challenging, especially with varying expert opinions. This study proposes a hybrid multicriteria decision-making (MCDM) approach combining the Pythagorean fuzzy method based on removal effects of criteria (PF-MEREC) and stepwise weight assessment ratio analysis (SWARA). By integrating both objective and subjective weight assessments, the approach ranks alternatives using TOPSIS. This method offers a novel solution to early childhood cancer diagnosis, demonstrating its practicality and efficiency through sensitivity analysis. The results align with the standards of the American Cancer Society and the National Cancer Institute, showcasing its potential to improve diagnosis and treatment planning.

1. Introduction

Childhood cancer is a multifaceted and often life-threatening medical condition characterized by the uncontrolled growth of cancerous cells or tumors, primarily affecting individuals under 18 years old. This condition can manifest in various parts of a child's body, including the blood, brain, bones and other vital organs. Although childhood cancer is less common than adult cancer, it remains a significant concern due to its profound impact on the well-being and overall health of affected children and their families. The gravity of this issue becomes particularly pronounced in less economically developed regions, where geography significantly influences the prognosis for pediatric cancer. In more affluent

2020 *Mathematics Subject Classification.* 34B24, 34B27.
Key words and phrases. Pythagorean fuzzy sets, Medical diagnosis, Childhood cancer, MEREC, SWARA, TOPSIS.
Received: 2024-08-12 Accepted: 2024-11-10.
* Corresponding author.

nations, the majority of children diagnosed with cancer have favorable outcomes, with approximately 80% or more achieving positive treatment results [35]. In contrast, children with cancer in low and middle income countries face significantly reduced survival prospects, with survival rates estimated at around 45%. Several factors contribute to this stark disparity, including delayed cancer diagnoses (often at advanced stages), limited financial resources for costly advanced treatments and challenges in accurately diagnosing and effectively treating the disease [13]. If poor and middle-income countries ensure that children have access to the right medicines and equipment for treatment, more lives can be saved. The best way to help children with cancer is to provide them with effective treatments based on proven methods, along with comprehensive care and support. Childhood cancer impacts children's physical health and profoundly affects the emotional and psychological well-being of both the children and their families. Coping with a cancer diagnosis, the demands of treatment and the uncertainty of the future can be incredibly challenging for children and their loved ones. Ongoing efforts focus on advancing research, improving diagnostic techniques and enhancing treatment options for childhood cancers. Organizations, healthcare professionals and advocates are committed to raising awareness and offering support to affected families. Many children diagnosed with cancer can go on to lead happy lives, despite the challenges they face. This is made possible by advancements in medical science and the unwavering support of their communities.

To enhance the likelihood of curing childhood cancer and minimize associated suffering and treatment expenses, it is imperative to identify cancer early and promptly initiate proper treatment. Early detection of cancer in children facilitates its management through interventions such as surgery, radiation and chemotherapy. The three crucial considerations for early identification are as follows:

(i) Parents should learn about childhood cancer to identify its symptoms and seek medical consultation if needed.
(ii) Healthcare professionals must act swiftly with proficiency to investigate and administer appropriate treatment.
(iii) Children must have immediate access to appropriate treatment when needed.

When cancer is found early, it is easier to recover and there is less financial and physical hardship. Low and middle-income countries should educate parents about childhood cancer with the help of knowledgeable doctors. This way, parents can act promptly if they notice symptoms in their children. Achieving this goal requires the cooperation of community organizations and non-governmental groups. In 2018, the World

Health Organization started a global effort to address childhood cancer. They offered guidance and support to governments in maintaining high-quality programs for childhood cancer care. The aim is to increase the survival rate of childhood cancer to at least sixty percent by 2030 [36].

2. Literature Review

In the realm of childhood cancer research, numerous studies have explored a wide range of facets related to this critical issue. These investigations have sought to shed light on the causes, trends, outcomes and impacts of childhood cancer, collectively contributing to a comprehensive understanding of this complex topic. In this concise narrative, we synthesize insights from various studies. Parkin et al. [39] delved into the causes of childhood tumors, highlighting viral infections and environmental exposures.

Miller et al. [33] emphasized the significance of precise histologic classification in understanding childhood cancer trends. Hamre et al. [15] focused on the early deaths of childhood cancer, exploring the influencing factors. Liu et al. [28] addressed the registration of children with cancer and proposed solutions for nationwide registries. Hudson et al. [19] examined the long-term health outcomes in childhood cancer survivors, emphasizing aging, lifestyle and genetics.

Klassen et al. [25] systematically reviewed the factors affecting the quality of life among children with cancer and survivors. Torabi et al. [48] compared methods for detecting clusters of childhood cancer cases, underscoring the importance of method selection. Staba et al. [16] highlighted the significance of specialized survivor clinics for managing health issues in childhood cancer survivors, despite regular primary care and oncology follow-up visits. Spector et al. [46] addressed the challenges in identifying the causes of childhood cancer, emphasizing inherent factors such as birth weight, parental age, birth defects and genetic variations.

Meanwhile, Rodriguez et al. [42] conducted a unique South American study, exploring space-time clustering of Acute Lymphoblastic Leukemia cases in Colombian children, hinting at potential localized environmental or infectious factors. Manrique et al. [32] focused on identifying clusters of non-leukemia childhood cancers in Colombia and suggested that environmental and occupational factors may contribute, Liu et al. [29] examined the impact of long non-coding RNAs on childhood cancer development and their potential use as early detection biomarkers. Ehrhardt et al. [12] highlighted the progress in treating childhood cancer through collaborative clinical trials and survivorship studies, while also noting ongoing health challenges for survivors and the importance

of personalized care. Deegan et al. [9] explored the significance of social support among childhood cancer survivors, despite mixed findings related to gender and age, which calls for more robust research in this area.

Horan et al. [17] underscored the importance of patient-reported outcome measures (PROMs) for monitoring the long-term effects of cancer treatment and provided considerations for their effective implementation. Dixon et al. [10] investigated the long-term health outcomes of childhood cancer survivors beyond 5 years post-diagnosis, emphasizing the risk of late mortality and the need for a healthy lifestyle. Huls et al. [21] sought to identify factors contributing to childhood cancer incidence, particularly the interplay of environmental and social factors. Huang et al. [18] examined global trends in childhood cancer incidence and mortality, highlighting disparities between high-income and low-income countries. Kumar et al. [44] provided updated cancer incidence data for India, emphasizing the importance of early detection and management in cancer control.

Van et al. [49] assessed the well-being of parents of long-term childhood cancer survivors, exploring their health-related quality of life, post-traumatic stress and post-traumatic growth. Mass et al. [30] investigated the psychosocial consequences of childhood cancer survivors, noting the generally positive impact of their experiences. Finally, Lemmen et al. [27] explored the long-term effects experienced by childhood cancer survivors in Africa, underlining the need for more research, particularly in psychosocial aspects. Together, these comprehensive studies contribute to a deeper understanding of childhood cancer, spanning its causes, consequences and potential avenues for improving care and support. Researchers have demonstrated unwavering dedication in unravelling the complexities surrounding this critical issue.

3. MCDM and Pythagorean Fuzzy Sets in Medical Diagnosis

Medical information is highly confidential and can sometimes be quite complex. Different experts may have varying opinions about a patient's health, making it challenging to arrive at a correct diagnosis. In such cases, fuzzy set theory [52] can be used to assist in the prognosis process. However, fuzzy sets have limitations when dealing with uncertainty, particularly when hesitancy is involved. Fuzzy sets only consider degrees of membership and non-membership. To address this limitation, Atanassov [5] introduced intuitionistic fuzzy sets, where the sum of membership and non-membership degrees is always one. Additionally, hesitancy is defined as one minus this sum. However, as time passed, it became evident that an extension of Intuitionistic fuzzy sets was needed

because they couldn't handle situations where the sum of membership and non-membership exceeded 1. Mathematically, suppose we denote the degrees of membership, non-membership and hesitancy degree as μ, ν and π, respectively. In that case, they should satisfy the conditions $\mu+\nu \leq 1$ and $\pi = 1-(\mu+\nu)$ for a set to be considered an Intuitionistic fuzzy set. However, when $\mu = \nu = \frac{1}{\sqrt{n}}$ for all values of $2 \leq n < 4$, the sum exceeds 1 and Intuitionistic fuzzy sets fail to handle such situations.

Recognizing this issue, Yager [51] introduced Pythagorean fuzzy sets (PFSs), which relax the condition to allow the square sum of membership and non-membership to be less than or equal to 1, thereby addressing these challenges. PFS, an extension of Intuitionistic fuzzy sets, offers a more comprehensive approach to handling uncertainty and vagueness in real-life scenarios, as evidenced by their recognition by researchers [8].

This development in the theory broadens its applicability in managing uncertainty in medical diagnoses and other fields. Childhood cancer is a critical aspect of healthcare-related MCDM and MCDM approaches can play a vital role in making well-informed, balanced and ethical decisions concerning the diagnosis, treatment and care of children with cancer. These approaches consider a wide range of factors that influence their health and well-being. MCDM approaches are indispensable in various medical applications, aiding in patient selection for disease diagnosis [26], choosing the most suitable face mask [31] and addressing diverse challenges.

For instance, Liu et al. [29] introduced the Pythagorean Fuzzy Combined Compromise Solution (PF-COCOSO) method to evaluate medical waste treatment technologies and Akram et al. [2] established a Pythagorean Fuzzy Elimination and Choice Translating Reality (PF-ELECTRE) model for handling risk assessment issues in the healthcare sector. Molla et al. [34] address diagnosing a patient's actual fever, framing it as an MCDM problem. Zhou et al. [56] introduce a novel divergence measure for Pythagorean fuzzy sets grounded in belief functions and its application in medical diagnosis. Xiao and Ding [50] introduce the novel PFSJS distance, based on Jensen–Shannon divergence, as a promising approach to measure Pythagorean fuzzy set discrepancies, demonstrating its effectiveness in addressing medical diagnosis challenges.

In MCDM, the allocation of the criteria weights is of paramount importance for well-informed decision-making. However, determining the underlying objective preferences for these weight assignments can sometimes pose challenges or prove undesirable. To address this concern, the MEREC methodology, as introduced by Keshavarz [24], assumes significant importance within the realm of MCDM. This method provides

a structured and objective framework for determining weights, taking into account the trade-offs between criteria, reducing uncertainty and ensuring a well-balanced outcome for decision-makers.

It presents a reliable means for decision-makers to establish objective weights that accurately represent the significance of various criteria within a decision-making context. Subjective weights are pivotal in MCDM, facilitating the integration of human judgment and qualitative insights into decision models. Thoughtfully and transparently assigned, these weights enhance the quality of decision outcomes, making them more context-specific and meaningful.

Additionally, Kersuliene et al. [23] have highlighted the value of the Stepwise Weight Assessment Ratio Analysis (SWARA) method in MCDM. SWARA empowers decision-makers to assign subjective weights based on their knowledge, preferences and insights, fostering a participatory approach that accurately captures collective judgment. Alipour et al. [3] employed a fusion of SWARA and Complex Proportional Assessment (COPRAS) to determine the most suitable suppliers for fuel cell and hydrogen components in the domain of PFS. Saraji et al. [43] introduced a novel method known as hesitant fuzzy-SWARA-MULTIMOORA for optimizing multi-objective decision-making in the context of online education.

Some researchers have explored strategies to amalgamate various methodologies for addressing decision-making challenges. For example, Rani et al. [40] introduced an innovative approach called the integrated SWARA-ARAS method, incorporating PFS for managing healthcare waste treatment issues and other real-life problems, such as mitigating Industry 4.0 risks [38], supplier disruption risks [47], etc.

Numerous experts in the field have devised various ranking methodologies to address the challenges associated with MCDM. Among these, the TOPSIS method, as introduced by Hwang and Yoon [20], has proven to be an invaluable tool in the realm of MCDM. This method stands out due to its systematic approach to evaluating alternative options based on their proximity to the optimal solution. Its capability to yield precise and comprehensible rankings is particularly beneficial for facilitating effective decision-making, aiding decision-makers in selecting the most suitable alternative while considering multiple criteria. This method has proven effective in various contexts, including the assessment of service quality in domestic airlines [55], the selection of energy projects [37], the procurement of smartphones for white-collar workers [4], selecting the optimal E-Learning platform for universities [1] and property acquisition [26], among other applications.

4. Motivation and Objectives

In the realm of childhood cancer research, numerous studies have made substantial contributions to our understanding of this critical issue. These investigations have delved into a broad spectrum of topics concerning childhood cancer, including its origins, patterns, outcomes and enduring effects. However, it is crucial to acknowledge that diagnosing childhood cancer can be intricate and demanding due to the sensitive nature of medical information and varying expert opinions.

A recent notable study by Habib et al. [14] introduced a Pythagorean fuzzy model tailored to assist in the early identification of the most probable type of cancer in children. This model considers symptoms associated with different types of childhood cancer. The Pythagorean fuzzy decision-making techniques employed in their study include TOPSIS, Pythagorean fuzzy entropy and Pythagorean Fuzzy Power Weighted Geometric (PFPWG). While the insights provided by Habib et al. [14] are valuable, it is noteworthy that the study did not delve into the discussion of objective and subjective weights, which are typically significant factors in MCDM. Objective and subjective weights play a crucial role in the accuracy of the decision-making process and their absence in the study may leave room for improvement in childhood cancer diagnosis.

The primary motivation behind this study lies in the creation of a novel hybrid PF-MEREC-SWARA-TOPSIS method capable of effectively handling the inherent vagueness and uncertainty associated with decision experts' judgments within the Pythagorean fuzzy domain. The summary of the article can be outlined as follows:

(i) Conduct a comprehensive study on childhood cancer diseases.
(ii) Develop an innovative hybrid (PF-MEREC-SWARA-TOPSIS) method specifically designed for application within the PF domain.
(iii) Decision experts' weights are calculated within the framework of the Pythagorean fuzzy set, using the formula introduced by Boran et al. [6].
(iv) Compute objective criteria weights through the MEREC method and subjective criteria weights using the SWARA method, then determine the combined criteria weight.
(v) The suggested approach is applied to identify specific childhood cancer diseases using the TOPSIS method. It is then subjected to a comparative evaluation with other established methods, followed by a sensitivity analysis considering a set of criteria weights.

The paper is structured as follows: Section 5 provides a fundamental overview of PFSs. In section 7, we delve into the examination of childhood cancer diseases and section 8 introduces an innovative MCDM approach applied to Pythagorean fuzzy sets. Section 9 showcases a practical real-world case study involving the identification of childhood cancer diseases to illustrate the effectiveness of our advanced method. This section also includes sensitivity analysis and a comparative evaluation of the results against existing methods to affirm the validity of our approach. Finally, within section 14, we delineate our findings and delve into prospective avenues for future research within this domain.

5. Preliminaries

This segment explores key definitions relevant to our study. We define X as the finite universal set and PFS(X) as the set containing all PFSs under consideration.

Definition 5.1 ([51])**.** An expression of a set $P = \{\langle x, \mu_P(x), \nu_P(x)\rangle : x \in X\}$ defined in X is called Pythagorean fuzzy set if

(i) $\mu_P : X \to [0,1]$ is membership degree,
(ii) $\nu_P : X \to [0,1]$ is non- membership degree,
(iii) $0 \leq \mu_P^2(x) + \nu_P^2(x) \leq 1$.

For a PFS $P \in X$, $\pi_P(x) = \sqrt{1 - \mu_P^2(x) - \nu_P^2(x)}$ is called hesitancy degree.

Definition 5.2 ([54])**.** The subsequent operations are well-defined for PFSs. Consider A and B as two PFSs in X and let $x \in X$ for all the properties mentioned below.

(i) $A = B$ iff $\mu_A(x) = \mu_B(x), \nu_A(x) = \nu_B(x)$,
(ii) $A \subseteq B$ iff $\mu_A(x) \leq \mu_B(x), \nu_A(x) \geq \mu_B(x)$,
(iii) $\overline{A} = \{\langle x, \nu_A(x), \mu_A(x)\rangle\}$, $\overline{A}$ = Complement of A ,
(iv) $A \cup B = \{\langle x, \max(\mu_A(x), \mu_B(x)), \min(\nu_A(x), \nu_B(x))\rangle\}$,
(v) $A \cap B = \{\langle x, \min(\mu_A(x), \mu_B(x)), \max(\nu_A(x), \nu_B(x))\rangle\}$.

Definition 5.3 ([55])**.** Suppose $\eta = Y(\mu_\eta, \nu_\eta)$ to be a Pythagorean fuzzy number (PFN). The score function of η are described as $S(\eta) = \mu_\eta^2 - \nu_\eta^2$, where $S(\eta) \in [-1,1]$. Since $S(\eta) \in [-1,1]$, Thus, PFN's score function has been modified as

$$S^\star(\eta) = \frac{1}{2}\left(\left(\mu_\eta^2 - \nu_\eta^2\right) + 1\right), \quad \text{where} \quad S^\star(\eta) \in [0,1]. \tag{5.1}$$

Definition 5.4 ([26])**.** Let A and B be two PFSs in X. Then, a weighted K-L divergence-based distance measure between A and B is

$$D^{w}_{\mathrm{kl}}(A,B) = \frac{1}{2n\log(2)}\sum_{i=1}^{n} W_i \left[\left(\mu_A^2(x_i) - \mu_B^2(x_i)\right)\log\frac{1+\mu_A^2(x_i)}{1+\mu_B^2(x_i)} + \left(\nu_A^2(x_i) - \nu_B^2(x_i)\right)\log\frac{1+\nu_A^2(x_i)}{1+\nu_B^2(x_i)}\right] \tag{5.2}$$

where $W = (W_1, W_2, \ldots, W_n)^T$ is the weight vector of x_i $(i = 1, 2, \ldots, n)$ with $W_i \in [0,1]$, $i = 1, 2, \ldots, n$, $\sum_{i=1}^{n} W_i = 1$.

6. Advantages of the Weighted K-L Divergence Distance Measure for Pythagorean Fuzzy Sets

The choice of the weighted K-L divergence distance measure for comparing PFSs can be justified for several reasons:

(i) **Sensitivity to uncertainty**: The domain of PFSs is larger compared to FSs and IFSs, making it better suited to handle uncertainty in real-life problems. The K-L divergence, particularly when weighted, effectively captures and quantifies this uncertainty, providing a more nuanced understanding of the differences between PFSs.

(ii) **Flexibility with weights**: The inclusion of weights in the distance measure allows for the consideration of the relative importance of different elements in the universe. This flexibility enables users to tailor the comparison based on specific application requirements or domain knowledge.

(iii) **Statistical soundness**: The K-L divergence is a well-established measure in information theory and statistics. Its mathematical foundation and properties ensure robustness and reliability in capturing the divergence between probability distributions, which aligns well with the probabilistic nature of PFSs.

(iv) **Comprehensive comparison**: By incorporating both membership and non-membership degrees into the distance measure, the weighted K-L divergence offers a comprehensive comparison of PFSs. It considers not only the degree of overlap between fuzzy sets but also their differences in uncertainty and hesitancy, providing a more holistic assessment.

(v) **Interpretability**: The weighted K-L divergence distance measure provides interpretable results by directly quantifying the

divergence between the membership and non-membership degrees of PFSs. This facilitates a clear understanding of the similarities and differences between PFSs.

Overall, the weighted K-L divergence distance measure stands out for its ability to handle uncertainty, flexibility with weights, statistical soundness, comprehensive comparison and interpretability, making it a suitable choice for comparing PFSs in various applications.

7. Type of Childhood Cancer Diseases

Below are some common types of childhood cancers, with brief descriptions provided in references [11, 33]. Figure 1 illustrates the various types of childhood cancer.

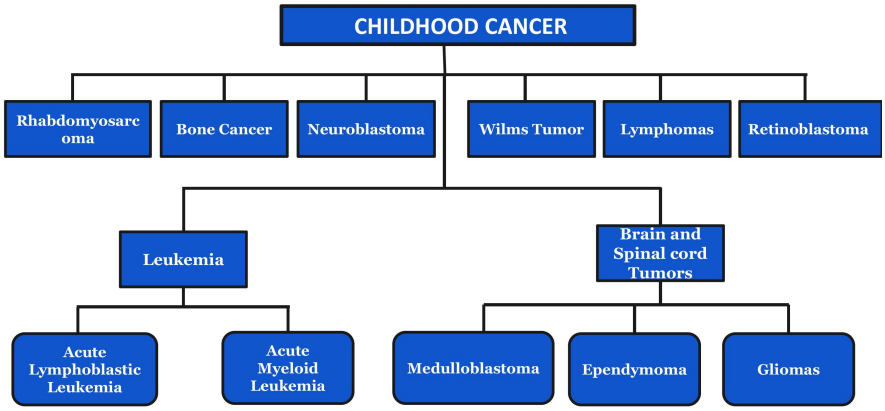


Figure 1. Flowchart of the Type of Childhood Cancer

- **Leukemia:** Leukemia is a type of cancer that kids can get. It starts in the blood and bones. There are two main types in kids: Acute Lymphoblastic Leukemia (ALL) and Acute Myeloid Leukemia (AML). Signs of leukemia in kids can include feeling very tired, getting bruises easily, getting sick a lot and having pain in the bones. Doctors often treat it with medicines such as chemotherapy and radiation; sometimes, they even put new cells from someone else into the kid's body to help them get better.
- **Brain and Central Nervous System (CNS) Tumors:** Brain tumors affecting children can develop in various regions of the brain, each with distinct symptoms. Common signs include

headaches, seizures, changes in vision and alterations in behavior. Treatment strategies may include surgical tumor removal, radiation therapy and chemotherapy. Below is a brief overview of the three common types of childhood brain and CNS tumors:
  - **Medulloblastoma:** A common childhood brain tumor found in the cerebellum, causing symptoms like headaches and balance issues. Treatment involves surgery, radiation and chemotherapy.
  - **Ependymoma:** Originating in brain ventricles, ependymomas lead to symptoms such as headaches and mood changes. Treatment includes surgery, radiation and chemotherapy.
  - **Astrocytoma:** These tumors develop from brain glial cells, causing headaches, seizures and behavioral changes. Treatment varies based on tumor type, involving surgery, radiation, chemotherapy, or targeted therapies.
- **Neuroblastoma:** Neuroblastoma is a type of cancer that starts in the nerves, often in the glands above the kidneys. It can make the tummy swell, cause discomfort and disrupt normal bowel or bladder function. Doctors treat it with surgery, medicine, radiation and sometimes by putting new cells in the body.
- **Wilms Tumor:** Wilms tumor is a kidney cancer predominantly found in young children. It typically presents as an abdominal swelling or lump. Treatment primarily consists of surgical removal of the tumor, followed by chemotherapy.
- **Lymphomas:** Lymphomas are a type of cancer that can affect kids and there are two main kinds: Hodgkin lymphoma and non-Hodgkin lymphoma. Signs of these cancers include having swollen lymph nodes, running a fever and losing weight. Doctors usually treat them with medicines like chemotherapy and radiation; sometimes, they might use stem cell transplants.
- **Retinoblastoma:** Retinoblastoma is a rare eye cancer impacting the retina and can lead to vision issues or, in severe cases, loss of the eye. Treatment options include surgery, chemotherapy and radiation therapy.
- **Rhabdomyosarcoma:** Rhabdomyosarcoma is a type of cancer that develops within the body's soft tissues, predominantly within muscles. This condition can manifest in different regions of the body, encompassing the head and neck, genitourinary system and limbs.
- **Bone Cancer:** Bone cancer is not very common but is a serious kind of cancer that mainly affects the bones. There are two main

types: one that starts in the bones and another that occurs when cancer from other parts of the body spreads to the bones.

8. A Novel Hybrid MCDM Methodology

In this section, we describe our proposed methodology. First, we explain how we determine objective weights using the MEREC method in subsection 8.1. Then, we discuss how we assign subjective weights using the SWARA method in subsection 8.2. These two methods come together in subsection 8.3 to calculate combined weights. Next, we clarify how we rank different options using the TOPSIS method in subsection 8.4. We call this comprehensive approach the PF-MEREC-SWARA-TOPSIS method for MCDM decision-making. A visual representation of the steps of this approach can be seen in Figure 2.

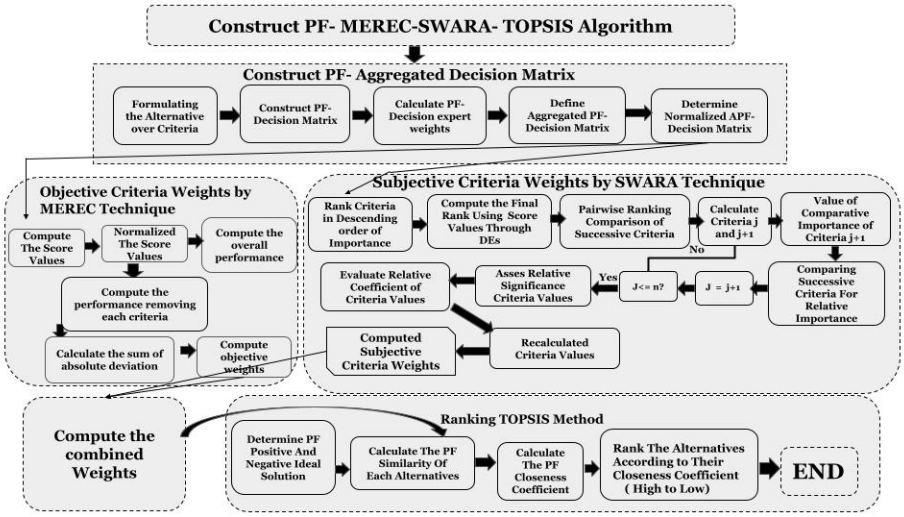


Figure 2. Representation of the PF- MEREC-SWARA- TOPSIS Technique for selection childhood cancer diseases

The algorithm includes the following steps.

Step 1: Formulating a decision matrix

In the MCDM process, we investigate a set of diseases (D) and symptoms (S), denoted as $D = \{D_1, D_2, \ldots, D_m\}$ and $S = \{S_1, S_2, \ldots, S_n\}$. To identify desirable diseases, we establish a set of decision experts (DEs) $E = \{E_1, E_2, \ldots, E_L\}$. Let $M = \left(g_{ij}^k\right)$, with $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$, be a decision matrix expressed by the DEs. It evaluates the m diseases with respect to the n symptoms by the k^{th} DEs.

Step 2: Determine the weights assigned to the DEs

To calculate the weights of DEs [6] in PFN, where $D_k = Y(\mu_k, \nu_k, \pi_k)$ for the k^{th} evaluation, we use equation (8.1).

$$W_k = \frac{\left(\mu_k^2 + \pi_k^2 \times \left(\frac{\mu_k^2}{\mu_k^2+\nu_k^2}\right)\right)}{\sum_{k=1}^{L}\left(\mu_k^2 + \pi_k^2 \times \left(\frac{\mu_k^2}{\mu_k^2+\nu_k^2}\right)\right)}, \quad k = 1, 2, \ldots, L; \tag{8.1}$$

$$\text{where,} \quad W_k \geq 0 \text{ and } \sum_{k=1}^{L} W_k = 1.$$

Step 3: Generation of the Aggregated Pythagorean Fuzzy decision (APFD) matrix: To create the APFD matrix, the individual decision matrices are combined into a single decision matrix using the opinions of DEs. This is achieved by employing the Pythagorean fuzzy weighted averaging (PFWA) operator [51]. The resulting APFD matrix, denoted as $Z = (z_{ij})_{m\times n}$, represents the consolidated decision matrix.

$$\begin{aligned} z_{ij} &= Y\left(\mu_{ij}, \nu_{ij}\right) \\ &= \text{PFWA}\left(g_{ij}^{(1)}, \ldots, g_{ij}^{(L)}\right) \\ &= Y\left(\sqrt{1 - \prod_{k=1}^{L}(1-\mu_k^2)^{W_k}}, \prod_{k=1}^{L}(\nu_k)^{W_k}\right), \end{aligned} \tag{8.2}$$

where μ_k, ν_k are membership and non- membership value, W_k is the weights of experts w. r. t k^{th} evaluations.

8.1. **The MEREC Method for Objective Weights.** To estimate the objective weights of criteria, we follow these steps.
Step 8.1a: Evaluate the score matrix $S^{\star}(\widetilde{z}_{kj})$ using equation (5.1) in Definition 5.3.
Step 8.1b: Analyze the normalized APFD matrix $M = (\widetilde{z_{ij}})_{m\times n}$, using equation (8.3), where

$$\widetilde{z_{ij}} = \begin{cases} \frac{\min\limits_k z_{kj}}{z_{ij}}, & j \in T_b \\ \\ \frac{z_{ij}}{\max\limits_k z_{kj}}, & j \in T_n \end{cases}, \quad i = 1, 2, \ldots, m. \tag{8.3}$$

T_b = beneficial sets and T_n = non-beneficial sets, respectively.
Step 8.1c: Evaluate the overall performance of each alternative
To calculate the overall performance of each alternative, equation (8.4)

is employed.

$$\psi_i = \ln\left(1 + \left(\frac{1}{n}\sum_{j=1}^{n} |\ln(\widetilde{z}_{ij})|\right)\right). \tag{8.4}$$

Step 8.1d: Assessing option performance via elimination of individual criteria
The evaluation of each option's performance entails individually eliminating each criterion, as described in equation (8.5).

$$\psi'_{ij} = \ln\left(1 + \left(\frac{1}{n}\sum_{r,r\neq j} |\ln(\widetilde{z}_{ir})|\right)\right), \tag{8.5}$$

where n = sets of performances w.r.t n criteria.
Step 8.1e: Calculating the removal impact of the j^{th} criterion
The removal impact of the j^{th} criterion, denoted by F_j, is determined as follows:

$$F_j = \sum_{i=1}^{m} \left|\psi'_{ij} - \psi_i\right|. \tag{8.6}$$

Step 8.1f: Calculate the objective weight of the criteria
We calculate the objective weight of the criteria using equation (8.7).

$$OW_j = \frac{F_j}{\sum_{j=1}^{n} F_j}. \tag{8.7}$$

8.2. **The SWARA Method for Subjective Weights:** To determine the subjective weight of the criteria, we follow these steps:
Step 8.2a: The conventional values of PFNs are established by assessing equation (5.1) outlined in Definition 5.3, resulting in the acquisition of the score values $S^{\star}(\widetilde{z}_{kj})$.
Step 8.2b: The criteria are ordered based on the preferences of the DEs, from the most significant to the least significant.
Step 8.2c: Comparing the criteria ranked in the second position will help determine the relative importance of the score values. The relative significance is determined by the difference between criteria j and $j-1$.
Step 8.2d: Calculate the relative coefficient by determining the coefficient k_j using the following equation (8.8).

$$k_j = \begin{cases} 1 & \text{if } j = 1, \\ s_j + 1 & \text{if } j > 1, \end{cases} \tag{8.8}$$

where s_j represents the relative significance of the score value [53].
Step 8.2e: Determine the weight estimate. The recalculated weight p_j is defined as:

$$p_j = \begin{cases} 1 & \text{if } j = 1, \\ \frac{k_{j-1}}{k_j} & \text{if } j > 1. \end{cases} \tag{8.9}$$

Step 8.2f: Evaluate the assigned subjective weight for each criterion. The subjective weights for the criteria are determined by:

$$SW_j = \frac{p_j}{\sum_{j=1}^{n} p_j}. \tag{8.10}$$

8.3. **Evaluate the Combined Criteria Weights.** Below is the provided formula that incorporates weighting, determined by both the objective and subjective importance of the criteria:

$$CW_j = \lambda(OW_j) + (1-\lambda)SW_j, \quad \lambda \in [0,1],\ j = 1, 2, \ldots, n. \tag{8.11}$$

8.4. **The TOPSIS Method for Alternatives Ranking.** To estimate the ranking of alternatives, we follow these steps:
Step 8.4a: Normalize the APFD matrix obtained by (8.2) using equation (8.12).

$$\begin{aligned} \widetilde{X_{ij}} &= Y\left(\widetilde{\mu_{ij}}, \widetilde{\nu_{ij}}\right) \\ &= \begin{cases} z_{ij} = Y\left(\mu_{ij}, \nu_{ij}\right) & j \in T_b \\ (z_{ij})^c = Y\left(\nu_{ij}, \mu_{ij}\right) & j \in T_n \end{cases}, \quad i = 1, 2, \ldots, m. \end{aligned} \tag{8.12}$$

where T_b = beneficial set and T_n = non-beneficial set, respectively.
Step 8.4b: Compute the PF positive and negative ideal solutions. Compute the PF positive and negative ideal solutions using equations (8.13) and (8.14), respectively.

$$\begin{aligned} P^{k+} &= \left\{ z_1^{k+}, z_2^{k+}, \ldots, z_n^{k+} \right\} \\ &= \left\{ \left(\max_i \left(z_{ij}^k \right), j \in T_b \right), \left(\min_i \left(z_{ij}^k \right), j \in T_n \right) \right\}. \end{aligned} \tag{8.13}$$

$$\begin{aligned} P^{k-} &= \left\{ z_1^{k-}, z_2^{k-}, \ldots, z_n^{k-} \right\} \\ &= \left\{ \left(\min_i \left(z_{ij}^k \right), j \in T_b \right), \left(\max_i \left(z_{ij}^k \right), j \in T_n \right) \right\}. \end{aligned} \tag{8.14}$$

Step 8.4c: Determine the PF distance of each alternative from both the positive and negative ideal solutions.

Calculate the PF distance of each alternative from the positive and negative ideal solutions using equations (8.15) and (8.16), respectively.

(8.15)
$$D^{w}_{\mathrm{kl}}(P_i, P_i^{+}) = \frac{1}{2n\log(2)} \sum_{i=1}^{n} CW_i \left[\left(\mu^2_{P_i}(x_i) - \mu^2_{P_i^{+}}(x_i) \right) \log \frac{1+\mu^2_{P_i}(x_i)}{1+\mu^2_{P_i^{+}}(x_i)} + \left(\nu^2_{P_i}(x_i) - \nu^2_{P_i^{+}}(x_i) \right) \log \frac{1+\nu^2_{P_i}(x_i)}{1+\nu^2_{P_i^{+}}(x_i)} \right].$$

(8.16)
$$D^{w}_{\mathrm{kl}}(P_i, P_i^{-}) = \frac{1}{2n\log(2)} \sum_{i=1}^{n} CW_i \left[\left(\mu^2_{P_i}(x_i) - \mu^2_{P_i^{-}}(x_i) \right) \log \frac{1+\mu^2_{P_i}(x_i)}{1+\mu^2_{P_i^{-}}(x_i)} + \left(\nu^2_{P_i}(x_i) - \nu^2_{P_i^{-}}(x_i) \right) \log \frac{1+\nu^2_{P_i}(x_i)}{1+\nu^2_{P_i^{-}}(x_i)} \right].$$

Step 8.4d: Calculate the PF closeness coefficient.
To find the closeness coefficient using equation (8.17).

(8.17)
$$R_i = \frac{D^{w}_{\mathrm{kl}}(P_i, P_i^{-})}{D^{w}_{\mathrm{kl}}(P_i, P_i^{-}) + D^{w}_{\mathrm{kl}}(P_i, P_i^{+})},$$

where $0 \leq R_i \leq 1$, $i = 1, 2, \ldots, n$.
Step 8.4e: Ranking the alternatives.
The ranking preference is evaluated from high to low for the alternatives.
Step 8.5: End of the procedure.

9. Application in Childhood Cancer Detection

This study focuses on eight different diseases: Leukemia (D_1), Rhabdomyosarcoma (D_8), Neuroblastoma (D_3), Wilms tumor (D_4), Brain and central nervous system tumors (D_5), Retinoblastoma (D_6), Lymphomas (D_7) and Bone cancer (D_2), in order to understand childhood cancer. A team of three experts has been selected to assist with this study. The evaluation criteria include eight different aspects, which are detailed in Table 1. The data used in this study are adopted from [14]. Here, we consider low risk for the beneficial category and high risk for the non-beneficial category.

TABLE 1. Childhood Cancer Risk Factors and Descriptions

Risk Factors	**Descriptions**	**Category**
Gender (S_1)	Gender is a demographic factor that may influence childhood disease occurrence.	Low risk
Age (S_2)	Childhood cancer risk varies with age, with certain cancers more common in specific age groups.	Low risk
Genetic disposition (S_3)	Family history or genetic mutations can significantly increase childhood cancer risk.	High risk
Autoimmune diseases (S_4)	Cancer risk are not strongly linked to autoimmune diseases, though the relationship may vary.	Low risk
Certain syndromes (S_5)	Genetic syndromes like Li-Fraumeni or Down syndrome increase childhood cancer risk.	High risk
Certain radiation exposure (S_6)	Ionizing radiation exposure from medical or environmental sources is a known cancer risk.	High risk
Certain chemical exposure (S_7)	Prolonged exposure to environmental chemicals can increase childhood cancer risk.	High risk
Socioeconomic status (S_8)	Socioeconomic factors affect childhood health, including access to healthcare and environmental exposures, which can influence cancer risk.	Low risk

In Table 2, linguistic terms have been associated with corresponding Pythagorean fuzzy numbers in the experts' opinion.

TABLE 2. Linguistic Terms and Corresponding Pythagorean Fuzzy Numbers

Linguistic Term	**Corresponding Pythagorean Fuzzy Number** $\langle \mu, \nu, \pi \rangle$
Very Low (VL)	$\langle 0, 1, 0 \rangle$
Low (L)	$\langle 0.2, 0.9, 0.39 \rangle$
Below Medium (BM)	$\langle 0.4, 0.6, 0.69 \rangle$
Medium (M)	$\langle 0.65, 0.50, 0.57 \rangle$
Above Medium (AM)	$\langle 0.8, 0.45, 0.4 \rangle$
High (H)	$\langle 0.9, 0.2, 0.39 \rangle$
Very High (VH)	$\langle 1, 0, 0 \rangle$

In Table 4, we present the assessment of each decision expert's weight, calculated using equation (8.1). In Table 3, with the help of expert opinion, we assign linguistic terms to diseases and symptoms. Subsequently, we associate Pythagorean fuzzy numbers with the data from Table 2 and aggregate it using equation (8.2) to consolidate the information into a single data set.

TABLE 3. Linguistic criteria of applications

Decision expert	**Symptoms**	**Diseases**							
		D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8
E_1	S_1	VL	L	M	M	M	L	AM	VL
	S_2	VH	L	M	M	M	M	M	M
	S_3	VH	M	BM	M	M	BM	M	M
	S_4	VH	L	VL	L	BM	L	L	L
	S_5	VL	BM	M	BM	L	L	L	VL
	S_6	VH	M	L	L	BM	M	BM	M
	S_7	VH	VL	L	L	L	L	VL	L
	S_8	VL	L	L	L	M	VL	L	VL
E_2	S_1	L	L	M	M	BM	L	M	L
	S_2	VH	L	M	M	M	BM	BM	BM
	S_3	H	M	BM	BM	BM	BM	BM	BM
	S_4	H	L	L	L	BM	VL	L	L
	S_5	L	M	BM	BM	L	L	L	L
	S_6	VH	BM	VL	L	BM	BM	BM	BM
	S_7	H	L	VL	L	L	L	L	L
	S_8	L	VL	L	L	BM	L	L	L
E_3	S_1	L	VL	BM	BM	BM	VL	M	L
	S_2	H	VL	BM	BM	BM	BM	BM	BM
	S_3	H	BM	BM	BM	M	BM	BM	M
	S_4	H	VL	L	VL	L	VL	VL	VL
	S_5	L	M	M	M	VL	VL	L	L
	S_6	VH	BM	VL	VL	BM	BM	M	BM
	S_7	H	L	VL	VL	VL	L	L	VL
	S_8	L	VL	VL	VL	M	L	VL	L

TABLE 4. Decision experts weights

Experts opinion	**Linguistic term**	**PFNs**	**Expert's weight**
High	H	$\langle 0.9, 0.2, 0.39\rangle$	0.4076
Above Medium	AM	$\langle 0.8, 0.45, 0.4\rangle$	0.3250
Medium	M	$\langle 0.65, 0.50, 0.57\rangle$	0.2674

OBJECTIVE WEIGHTS BY MEREC METHOD

The score value matrix obtained with the help of equation (5.1) is shown in Table 6.

Step 8.1b: Normalize APFD Matrix: To ensure consistency and comparability throughout the evaluation process, a standardized APFD matrix, $M = (\widetilde{z_{ij}})_{m\times n}$, is created using equation (8.3). This matrix accounts for the high risk of symptoms S_3, S_5, S_6 and S_7, while categorizing the remaining symptoms as low risk. Table 7 displays the normalized APFD matrix.

TABLE 5. Aggregated Pythagorean fuzzy decision matrix

Symptoms	**Diseases**			
	D_1	D_2	D_3	D_4
S_1	$Y(0.1546, 0.9395)$	$Y(0.1716, 0.9257)$	$Y(0.6014, 0.5250)$	$Y(0.6014, 0.5250)$
S_2	$Y(1, 0)$	$Y(0.1716, 0.9257)$	$Y(0.6014, 0.5250)$	$Y(0.6014, 0.5250)$
S_3	$Y(1, 0)$	$Y(0.6014, 0.5250)$	$Y(0.4000, 0.6000)$	$Y(0.5282, 0.5570)$
S_4	$Y(1, 0)$	$Y(0.1716, 0.9257)$	$Y(0.1546, 0.9395)$	$Y(0.1716, 0.9257)$
S_5	$Y(0.1546, 0.9395)$	$Y(0.5720, 0.5386)$	$Y(0.5895, 0.5305)$	$Y(0.4900, 0.5714)$
S_6	$Y(1, 0)$	$Y(0.5282, 0.5570)$	$Y(0.1285, 0.9580)$	$Y(0.1716, 0.9257)$
S_7	$Y(1, 0)$	$Y(0.1546, 0.9395)$	$Y(0.1285, 0.9580)$	$Y(0.1716, 0.9257)$
S_8	$Y(0.1546, 0.9395)$	$Y(0.1285, 0.9580)$	$Y(0.1716, 0.9257)$	$Y(0.1716, 0.9257)$
	D_5	D_6	D_7	D_8
S_1	$Y(0.5282, 0.5570)$	$Y(0.1716, 0.9257)$	$Y(0.7237, 0.4790)$	$Y(0.1546, 0.9395)$
S_2	$Y(0.6014, 0.5250)$	$Y(0.5282, 0.5570)$	$Y(0.5282, 0.5570)$	$Y(0.5282, 0.5570)$
S_3	$Y(0.5897, 0.5305)$	$Y(0.4000, 0.6000)$	$Y(0.5282, 0.5570)$	$Y(0.5897, 0.5305)$
S_4	$Y(0.3598, 0.6687)$	$Y(0.1285, 0.9580)$	$Y(0.1716, 0.9257)$	$Y(0.1716, 0.9257)$
S_5	$Y(0.1716, 0.9257)$	$Y(0.1716, 0.9257)$	$Y(0.2000, 0.9000)$	$Y(0.1546, 0.9395)$
S_6	$Y(0.4000, 0.6000)$	$Y(0.5282, 0.5570)$	$Y(0.4900, 0.5714)$	$Y(0.5282, 0.5570)$
S_7	$Y(0.1716, 0.9257)$	$Y(0.2000, 0.9000)$	$Y(0.1546, 0.9395)$	$Y(0.1716, 0.9257)$
S_8	$Y(0.5895, 0.5305)$	$Y(0.1546, 0.9395)$	$Y(0.1716, 0.9257)$	$Y(0.1546, 0.9395)$

TABLE 6. Score Matrix for MEREC Technique

Symptoms	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8
S_1	0.0706	0.0863	0.5430	0.5430	0.4844	0.0863	0.6472	0.0706
S_2	1.0000	0.0863	0.5430	0.5430	0.5430	0.4844	0.4844	0.4844
S_3	1.0000	0.5430	0.4000	0.4844	0.5332	0.4000	0.4844	0.5332
S_4	1.0000	0.0863	0.0706	0.0863	0.3411	0.0494	0.0863	0.0863
S_5	0.0706	0.5185	0.5330	0.4568	0.0863	0.0863	0.1150	0.0706
S_6	1.0000	0.4844	0.0494	0.0863	0.4000	0.4844	0.4568	0.4844
S_7	1.0000	0.0706	0.0494	0.0863	0.0863	0.1150	0.0706	0.0863
S_8	0.0706	0.0570	0.0863	0.0863	0.5330	0.0706	0.0863	0.0706

TABLE 7. Normalized APFD Matrix by MEREC Technique

Symptoms	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8
S_1	1.0000	0.8181	0.1300	0.1300	0.1457	0.8181	0.1091	1.0000
S_2	0.0863	1.0000	0.1589	0.1589	0.1589	0.1782	0.1782	0.1782
S_3	1.0000	0.5430	0.4000	0.4844	0.5332	0.4000	0.4844	0.5332
S_4	0.0494	0.5724	0.6997	0.5724	0.1448	1.0000	0.5724	0.5724
S_5	0.1325	0.9728	1.0000	0.8570	0.1619	0.1619	0.2158	0.1325
S_6	1.0000	0.4844	0.0494	0.0863	0.4000	0.4844	0.4568	0.4844
S_7	1.0000	0.0706	0.0494	0.0863	0.0863	0.1150	0.0706	0.0863
S_8	0.8074	1.0000	0.6605	0.6605	0.1069	0.8074	0.6605	0.8074

Step 8.1c: The comprehensive performance of the alternatives, as indicated by equation (8.4), yields $\psi_1 = 0.7314$, $\psi_2 = 0.9719$, $\psi_3 = 0.4970$, $\psi_4 = 0.6633$, $\psi_5 = 0.7770$, $\psi_6 = 0.7731$, $\psi_7 = 1.1718$, $\psi_8 = 0.4156$.

Step 8.1d: Table 8 illustrates the outcomes derived from utilizing equation (8.5) to assess the effectiveness of various options following the elimination of each criterion.

TABLE 8. Assessing Alternative Performance Through the Elimination of Each Criterion

Symptoms	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8
S_1	0.7314	0.7192	0.6004	0.6004	0.6082	0.7192	0.5884	0.7314
S_2	0.8487	0.9719	0.8808	0.8808	0.8808	0.8868	0.8868	0.8868
S_3	0.4970	0.4495	0.4248	0.4403	0.4480	0.4248	0.4403	0.4480
S_4	0.4480	0.6267	0.6400	0.6267	0.5304	0.6633	0.6267	0.6267
S_5	0.6535	0.7754	0.7770	0.7681	0.6664	0.6664	0.6847	0.6535
S_6	0.7731	0.7304	0.5825	0.6207	0.7188	0.7304	0.7269	0.7304
S_7	1.1718	1.0635	1.0479	1.0721	1.0721	1.0843	1.0635	1.0721
S_8	0.3978	0.4156	0.3808	0.3808	0.2117	0.3978	0.3808	0.3978

Step 8.1e: The absolute deviation calculated using equation (8.6) are $F_j = \{0.4798, 0.2489, 0.6669, 0.6112, 0.8647, 0.4281, 0.6030, 0.4544\}$. Now finally the objective weights derived from equation (8.7) are

(9.1)
$$OW_j = \{0.1101, 0.0571, 0.1531, 0.1403, 0.1985, 0.0983, 0.1384, 0.1043\}$$

10. Subjective Weights Determined Using the SWARA Method

To determine the subjective weights, each expert provides their opinion on each symptom. We then aggregate all the linguistic terms using equation (8.2). Finally, we evaluate the score values using equation (5.1) from Definition 5.3. The evaluated results are shown in Table 9.

TABLE 9. Criteria Weighting for Childhood Cancer Disease by Decision Experts Using Linguistic Variables

Symptoms	**Decision Experts**			**Aggregated PFNs**	**Score Values**
	E_1	E_2	E_3		
S_1	H	AM	AM	$Y(0.8500, 0.3233)$	0.8090
S_2	M	H	M	$Y(0.7731, 0.3712)$	0.7299
S_3	H	AM	AM	$Y(0.8500, 0.3233)$	0.8090
S_4	M	M	H	$Y(0.7556, 0.3913)$	0.7089
S_5	M	H	M	$Y(0.7731, 0.3712)$	0.7299
S_6	H	M	AM	$Y(0.8225, 0.3346)$	0.7823
S_7	AM	M	H	$Y(0.8038, 0.3749)$	0.7528
S_8	M	H	AM	$Y(0.8034, 0.3609)$	0.7576

Finally, subjective weight for criteria are

$$SW_j = \{0.1253, 0.1253, 0.1220, 0.1256, 0.1278, 0.1231, 0.1282, 0.1227\}$$

TABLE 10. Outcome of Subjective Weight Using the SWARA Method

Symptoms	**Score Values**	s_j	k_j	p_j	SW_j
S_1	0.8090	-	1.0000	1.0000	0.1253
S_3	0.8090	0.0000	1.0000	1.0000	0.1253
S_6	0.7823	0.0267	1.0267	0.9740	0.1220
S_8	0.7576	0.0247	1.0247	1.0020	0.1256
S_7	0.7528	0.0048	1.0048	1.0198	0.1278
S_5	0.7299	0.0229	1.0229	0.9823	0.1231
S_2	0.7299	0.0000	1.0000	1.0229	0.1282
S_4	0.7089	0.0210	1.0210	0.9794	0.1227

Step 8.3: The combined criteria weight set ($\lambda = 0.5$) is

$$CW_j = \{0.1177, 0.0912, 0.1376, 0.1330, 0.1632, 0.1107, 0.1333, 0.1135\}.$$

11. TOPSIS Method for Alternative Ranking

The normalized aggregated matrix in Table 11 is obtained using equation (8.12). Then using equations (8.13) and (8.14), We can calculate the best and minimum optimal values for pediatric cancer patients as follows:

$$P^{k+} = \{Y(0.7237, 0.4790), Y(1,0), Y(0,1), Y(1,0), Y(0.53055, 0.5895), Y(0,1), Y(0,1), Y(0.5895, 0.5305)\}.$$

and

$$P^{k-} = \{Y(0.1546, 0.9395), Y(0.1716, 0.9257), Y(0.6000, 0.4000), Y(0.1285, 0.9580), Y(0.9395, 0.1546), Y(0.9580, 0.1285), Y(0.9580, 0.1285), Y(0.1285, 0.9580)\}.$$

In Table 12, we conducted a comprehensive analysis to assess the severity of symptoms for each disease.

This was achieved by calculating the distance between the most and least favorable symptom values using equations (8.15) and (8.16). Subsequently, this distance method was applied to compute the Pythagorean fuzzy closeness coefficient values for each disease, as defined in equation (8.17). This coefficient serves as a valuable indicator of how closely a disease's symptom profile matches the ideal presentation we sought, essentially quantifying the similarity between a disease's symptom profile and the desired pattern. After concluding this analysis, we made a significant observation: Disease D_1 has emerged as the top disease,

boasting an outstanding PF closeness coefficient of **0.8201**, with the following ranking order: $D_1 > D_5 > D_7 > D_3 > D_4 > D_2 > D_8 > D_6$. This observation emphasizes the prominence of disease **Leukemia** (D_1) in comparison to all the other diseases we have examined. In simpler terms, it exhibits the closest resemblance to the ideal symptom pattern we were investigating. This finding underscores the significance of disease D_1 within the context of our study.

TABLE 11. Normalized aggregated Pythagorean fuzzy approach by TOPSIS method

Symptoms	**Diseases**			
	D_1	D_2	D_3	D_4
S_1	$Y(0.1546, 0.9395)$	$Y(0.1716, 0.9257)$	$Y(0.6014, 0.5250)$	$Y(0.6014, 0.5250)$
S_2	$Y(1, 0)$	$Y(0.1716, 0.9257)$	$Y(0.6014, 0.5250)$	$Y(0.6014, 0.5250)$
S_3	$Y(0, 1)$	$Y(0.5250, 0.6014)$	$Y(0.6000, 0.4000)$	$Y(0.5570, 0.5282)$
S_4	$Y(1, 0)$	$Y(0.1716, 0.9257)$	$Y(0.1546, 0.9395)$	$Y(0.1716, 0.9257)$
S_5	$Y(0.9395, 0.1546)$	$Y(0.5386, 0.5720)$	$Y(0.5305, 0.5895)$	$Y(0.5714, 0.4900)$
S_6	$Y(0, 1)$	$Y(0.5570, 0.5282)$	$Y(0.9580, 0.1285)$	$Y(0.9257, 0.1716)$
S_7	$Y(0, 1)$	$Y(0.9395, 0.1546)$	$Y(0.9580, 0.1285)$	$Y(0.9257, 0.1716)$
S_8	$Y(0.1546, 0.9395)$	$Y(0.1285, 0.9580)$	$Y(0.1716, 0.9257)$	$Y(0.1716, 0.9257)$
	D_5	D_6	D_7	D_8
S_1	$Y(0.5282, 0.5570)$	$Y(0.1716, 0.9257)$	$Y(0.7237, 0.4790)$	$Y(0.1546, 0.9395)$
S_2	$Y(0.6014, 0.5250)$	$Y(0.5282, 0.5570)$	$Y(0.5282, 0.5570)$	$Y(0.5282, 0.5570)$
S_3	$Y(0.5305, 0.5897)$	$Y(0.6000, 0.4000)$	$Y(0.5570, 0.5282)$	$Y(0.5305, 0.5897)$
S_4	$Y(0.3598, 0.6687)$	$Y(0.1285, 0.9580)$	$Y(0.1716, 0.9257)$	$Y(0.1716, 0.9257)$
S_5	$Y(0.9257, 0.1716)$	$Y(0.9257, 0.1716)$	$Y(0.9000, 0.2000)$	$Y(0.9395, 0.1546)$
S_6	$Y(0.6000, 0.4000)$	$Y(0.5570, 0.5282)$	$Y(0.5714, 0.4900)$	$Y(0.5570, 0.5282)$
S_7	$Y(0.9257, 0.1716)$	$Y(0.9000, 0.2000)$	$Y(0.9395, 0.1546)$	$Y(0.9257, 0.1716)$
S_8	$Y(0.5895, 0.5305)$	$Y(0.1546, 0.9395)$	$Y(0.1716, 0.9257)$	$Y(0.1546, 0.9395)$

TABLE 12. Evaluating the closeness coefficient and ranking the Disease

Diseases	$D_{\mathrm{KL}}^{W}(P_i, P_i^{+})$	$D_{\mathrm{KL}}^{W}(P_i, P_i^{-})$	R_i	**Ranking** ($\lambda = 0.5$)
D_1	0.0131	0.0597	0.8201	1
D_2	0.0546	0.0079	0.1264	6
D_3	0.0552	0.0108	0.1636	4
D_4	0.0510	0.0098	0.1612	5
D_5	0.0393	0.0132	0.2514	2
D_6	0.0554	0.0050	0.0828	8
D_7	0.0485	0.0100	0.1709	3
D_8	0.0527	0.0054	0.0929	7

12. Sensitivity Analysis

To assess the robustness and reliability of our findings, we conducted a sensitivity analysis.

Sensitivity analysis is a crucial step in our research, as it allows us to investigate how variations in input parameters or assumptions impact the outcomes. In the context of MCDM, it involves testing how different factors and choices affect our final decision. MCDM plays a vital role in aiding our decision-making process when faced with a multitude of considerations.

In this section, we conduct a thorough exploration by varying the parameter λ in the combined criteria weight, as specified in equation (8.11). This variation results in a diverse range of criteria weights, visually represented in Figure 3.

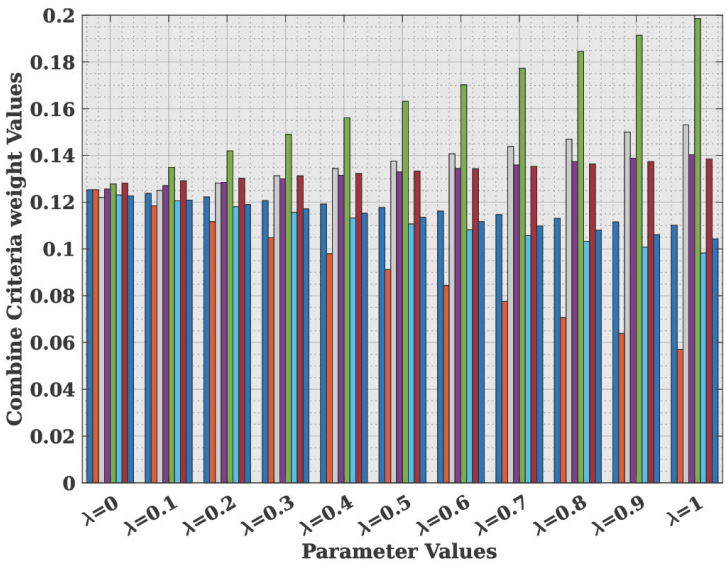


Figure 3. Combine criteria weight values for varying the parameter λ on each Diseases

These sets of criteria weights are then used to determine the final ranking of diseases, as shown in Figure 4. This analytical approach provides valuable insights into how the parameter λ influences the ultimate order of alternatives, offering a nuanced understanding of the decision-making landscape. Notably, in Figure 4, D_1 exhibits higher values than the others, with a ranking order of $D_1 > D_5 > D_7 > D_3 > D_4 > D_2 > D_8 > D_6$. This observation highlights the stability of our proposed

method, as it consistently produces the same ranking order despite variations in the parameter λ. This result reinforces the robustness of our methodology and underscores its potential for practical applications.

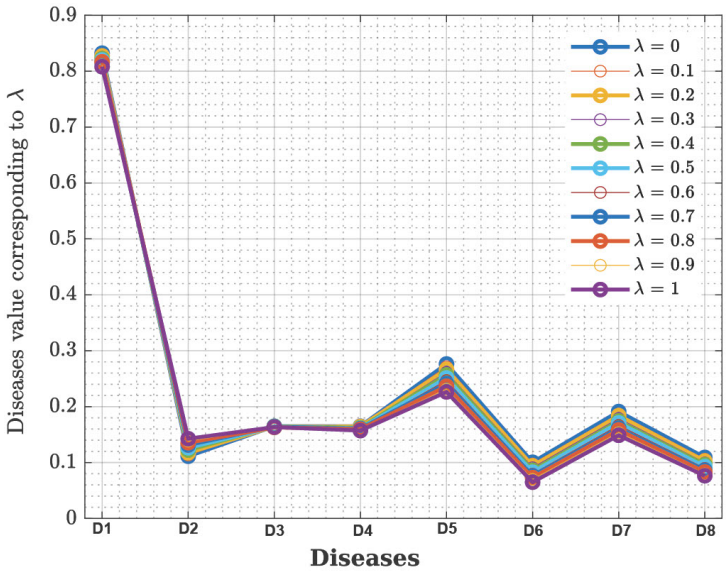


FIGURE 4. Ranking of Diseases for different parameter λ values

13. Comparative Analysis and Discussion

In this section, we assess the proposed methodology in comparison to existing ones by using the same example. The results are shown in Table 13.

TABLE 13. The comparative study with existing techniques

Methods	Standard	Experts weight	Criteria weight	Ranking	Evaluated disease
Zhang and Xu [55]	PF-TOPSIS Method	Not evaluate	Assumed	$D_5 > D_1 > D_7 > D_8 > D_2 > D_4 > D_3 > D_6$	D_5
Rani et al. [41]	PF-SWARA-VIKOR Method	Evaluate	Subjective Weight	$D_1 > D_5 > D_3 > D_7 > D_4 > D_8 > D_2 > D_6$	D_1
Chaurasiya and Jain [7]	PF-MEREC-SWARA-COPRAS Method	Evaluate	Combine weight	$D_1 > D_5 > D_7 > D_4 > D_3 > D_2 > D_6 > D_8$	D_1
Habib et al. [14]	PF-Entropy-PFPWG-TOPSIS Method	Evaluate	Objective weight	$D_1 > D_5 > D_3 > D_4 > D_7 > D_2 > D_8 > D_6$	D_1
Proposed Methodology	PF-MEREC-SWARA-TOPSIS Method	Evaluate	Combine weight	$D_1 > D_5 > D_7 > D_3 > D_4 > D_2 > D_8 > D_6$	D_1

Notably, the existing methodology overlooks considerations of expert and criteria weights essential aspects that contribute to variations in disease rankings when compared to our proposed approach. A detailed comparison of the existing methodology is provided below:

- In the methodology described by Zhang and Xu [55], the PF-TOPSIS method does not incorporate expert opinions and relies on assumed criteria weights. Consequently, the ranking order of diseases may vary when compared to the methodology employing PF-MEREC-SWARA-TOPSIS, which includes expert opinions and established criteria weight determination. Despite these differences in approach, a noteworthy consistency emerges in the ranking of diseases across these methods. As a result, disease D_5 maintains its top position compared to other diseases.
- In the methodology of Rani et al. [41], the employment of the PF-SWARA-VIKOR method is characterized by the absence of objective weights. As a result, the ranking of diseases may exhibit variability compared to methodologies that incorporate expert opinions and employ established criteria weight determination, as seen in PF-MEREC-SWARA-TOPSIS. Nevertheless, despite these differing approaches, a notable consistency emerges in the ranking of diseases. Disease D_1 consistently maintains its top position, thus highlighting its significance within the framework of these evaluation methods.
- In the methodology presented by Habib et al. [14], the use of PF-Entropy, PF-PFPWG and PF-TOPSIS methods is characterized by the absence of subjective weights. Consequently, the ranking of diseases may vary compared to methodologies that incorporate expert opinions and utilize established criteria weight determination, as demonstrated in PF-MEREC-SWARA-TOPSIS. On the other hand, Chaurasiya et al. [7] incorporate expert and criteria weights in their methodology. However, due to the sensitivity of subjective weight assignments, which may lead to bias and the computational complexity of the COPRAS method, the disease ranking differs from that obtained with our proposed methodology. Notably, D_1 is identified as a superior disease compared to others.
- The practical implications of the presented method offer valuable insights into the assessment of symptoms and diseases in childhood cancer. As demonstrated in Table 13, the most notable observation pertains to the effectiveness of managing childhood cancer. Specifically, we identify "disease D_1" among the existing diseases and its symptoms closely correspond to those

of childhood cancer, providing a valuable tool for early intervention and treatment of pediatric cancer patients. The findings in this paper have the potential to significantly contribute to addressing the challenges associated with childhood cancer.

Note: Our analysis aligns with data from the American Cancer Society (ACS) [45]. According to the ACS, 28% of children diagnosed with cancer suffer from leukemia, making it one of the most prevalent cancers among pediatric cases. Similarly, the National Cancer Institute (NCI) [22] reports that leukemia is the most commonly diagnosed cancer in children aged 0 to 14 years. The results presented in Table 14 below demonstrate the strength of our hybrid methodology.

TABLE 14. Ranking of ACS and NCI for childhood cancer

Diseases Name	**American Cancer Society**	**National Cancer Institute**
Leukemia (D_1)	28.1%	28%
Brain and Central Nervous System Tumors (D_5)	26.2%	26%
Lymphomas (D_7)	8.6%	8%
Neuroblastoma (D_3)	6.2%	6%
Wilms Tumor (D_4)	5.6%	5%
Rhabdomyosarcoma (D_2)	3.1%	3%
Bone Cancers (D_8)	2.8%	3%
Retinoblastoma (D_6)	2.8%	2%
Ranking	$D_1 > D_5 > D_7 > D_3 > D_4 > D_2 > D_8 > D_6$	$D_1 > D_5 > D_7 > D_3 > D_4 > D_2 > D_8 > D_6$

14. CONCLUSION

Medical information is both highly confidential and inherently complex, often leading to challenges in diagnosing a patient's condition, exacerbated by varying expert opinions. The notion of Pythagorean fuzzy sets introduces an innovative mathematical framework within the fuzzy domain, particularly effective at addressing uncertainty in decision-making processes. While Pythagorean fuzzy sets have found various applications in the literature, our focus on medical childhood cancer is especially relevant in the current scenario. This article presents an innovative approach to medical diagnosis, utilizing a hybrid MCDM framework within the Pythagorean fuzzy environment. Our method combines the Pythagorean fuzzy method, based on the removal effects of criteria (PF-MEREC), with the stepwise weight assessment ratio analysis (SWARA) technique, integrating both objective and subjective weight assessments.

Consequently, our approach generates preference order rankings for different alternatives within the Pythagorean fuzzy context using the technique for order of preference by similarity to the ideal solution (TOPSIS) framework. This innovative model synthesizes elements from the MEREC, SWARA and TOPSIS methods.

Importantly, our model is applied to expedite the early identification of childhood cancer diseases, accelerating treatment for patients. The article incorporates a sensitivity analysis, establishing a ranking order as follows: $D_1 > D_5 > D_7 > D_3 > D_4 > D_2 > D_8 > D_6$. Notably, D_1 has higher values than the others. The article also includes comparative discussions aimed at evaluating the practicality and efficiency of our proposed model in contrast to existing techniques. This aligns with the standards of the American Cancer Society and the National Cancer Institute, showcasing the strength of the proposed methodology.

Future scope. In the future, our research can extend its scope to encompass a wider range of Pythagorean fuzzy sets and diverse MCDM methodologies, promising even more enhanced results. To improve the medical diagnosis model, continuous learning through regular updates with real-world clinical data is advised.

Exploring advanced machine learning techniques, improving model interpretability and addressing biases in diverse patient populations are key focus areas. Additionally, conducting thorough validation studies across healthcare institutions is crucial for ensuring the model's generalizability and effectiveness in real-world applications.

List of Abbreviations

Table 15. Abbreviations and their full forms

Abbreviation	**Full form**
PF	Pythagorean fuzzy
MCDM	Multicriteria decision making
MEREC	Method based on the removal effects of criteria
SWARA	Stepwise weight assessment ratio analysis
TOPSIS	Technique for order of preference by similarity to the ideal solution
PFS	Pythagorean fuzzy sets
COCOSO	Combined compromise solution
ELECTRE	Elimination and choice translating reality
COPRAS	Complex proportional assessment
MULTIMOORA	Multiple objective optimization on the basis of ratio analysis
ARAS	Ascending reticular activating system
PFPWG	Pythagorean fuzzy power weighted geometric
PFN	Pythagorean fuzzy number
ALL	Acute lymphoblastic leukemia
AML	Acute myeloid leukemia
CNS	Central nervous system
DEs	Decision experts
APFD	Aggregated Pythagorean fuzzy decision
PFWA	Pythagorean fuzzy weighted averaging

Authorship Credit Contribution Statement:

Naveen Kumar: Writing - original draft, Software, Investigation, Formal analysis, Data curation. **Juthika Mahanta:** Writing - review and editing, Supervision.

Acknowledgment: The authors wish to thank Dr. Anirudha Dewri for his invaluable support in reviewing the content of this manuscript. We also appreciate the constructive feedback and helpful suggestions from the referees and editors, which greatly improved this paper.

Declaration of conflicting interests: The authors assert that they possess no identifiable financial interests or personal relationships that might have influenced the objectivity of the research presented in this paper.

Data availability: All the data employed in this manuscript have already been cited.

Funding: This study received no financial support.

References

1. I. Akargöl, I. Karadağ and Ö.F. Gürcan, *Selecting the optimal e-learning platform for universities: A Pythagorean fuzzy ahp/topsis evaluation*, Eur. J. Res. Dev., 4 (2024), pp. 19-34.
2. M. Akram, A. Luqman and J.C.R. Alcantud, *An integrated ELECTRE-I approach for risk evaluation with hesitant Pythagorean fuzzy information*, Expert Syst. Appl., 200 (2022), pp. 116945.
3. M. Alipour, R. Hafezi, P. Rani, M. Hafezi and A. Mardani, *A new Pythagorean fuzzy-based decision-making method through entropy measure for fuel cell and hydrogen components supplier selection*, Energy, 234 (2021), pp. 121208.
4. H.D. Arora and A. Naithani, *On some new fuzzy entropy measure of Pythagorean fuzzy sets for decision-making based on an extended TOPSIS approach*, J. Manag. Anal., 11 (1) (2024), pp. 87-109.
5. K.T. Atanassov, *Intuitionistic fuzzy sets*, Fuzzy Sets Syst., 20 (1) (1986), pp. 87-96.
6. F.E. Boran, S. Genç, M. Kurt and D.Akay, *A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method*, Expert Syst. Appl., 36 (8) (2009), pp. 11363-11368.
7. R. Chaurasiya and D. Jain, *Hybrid MCDM method on Pythagorean fuzzy set and its application*, Decis. Mak. Appl. Manag. Eng., 6 (1) (2023), pp. 379-398.
8. T.Y. Chen, *New Chebyshev distance measures for Pythagorean fuzzy sets with applications to multiple criteria decision analysis using an extended ELECTRE approach*, Expert Syst. Appl., 147 (2020), pp. 113164.

9. A. Deegan, C. Brennan, P. Gallagher, V. Lambert and S. Dunne, *Social support and childhood cancer survivors: a systematic review*, Psychosoc. Oncol., 32 (6) (2023), pp. 819-833.
10. S.B. Dixon, Q. Liu, E.J. Chow, K.C. Oeffinger, P.C. Nathan, R.M. Howell, W.M. Leisenring, M.J. Ehrhardt, K.K. Ness, K.R. Krull, et al., *Specific causes of excess late mortality and association with modifiable risk factors among survivors of childhood cancer: a report from the Childhood Cancer Survivor Study cohort*, Lancet, 401 (10386) (2023), pp. 1447-1457
11. G.J. Draper, M.E. Kroll and C.A. Stiller, *Childhood cancer*, Cancer Surv., 19 (1994), pp. 493-517.
12. M.J. Ehrhardt, K.R. Krull, N. Bhakta, Q. Liu, Y. Yasui, L.L. Robison and M.M. Hudson, *Improving quality and quantity of life for childhood cancer survivors globally in the twenty-first century*, Nat. Rev. Clin. Oncol., 20 (10) (2023), pp. 678-696.
13. S. Gupta, S.C. Howard, S.P. Hunger, F.G. Antillon, M.L. Metzger, T. Israels, M. Harif and C.R. Galindo., *Treating Childhood Cancer in Low- and Middle-Income Countries*, Cancer, 3 (2015), pp. 121-46.
14. S. Habib, M. Akram and M.M. Ali Al-Shamiri, *Comparative analysis of Pythagorean MCDM methods for the risk assessment of childhood cancer*, Comput. Model. Eng. Sci., 135 (3) (2023).
15. M.R. Hamre, J. Williams, P. Chuba, K. Bhambhani, Y. Ravindranath and R.K. Severson, *Early deaths in childhood cancer*, Med. Pediatr. Oncol., 34 (5) (2000), pp. 343-347.
16. S. Hogan, M. Jane, M. Xiaomei and K. Lottick, S.Nina *New health conditions identified at a regional childhood cancer survivor clinic visit*, Pediatr. Blood Cancer, 60 (4) (2013), pp. 682-687.
17. M.R. Horan, J.A. Sim, K.R. Krull, K.K. Ness, Y. Yasui, L.L. Robison, M.M. Hudson, J.N. Baker and I.C. Huang, *Ten Considerations for Integrating Patient-Reported Outcomes into Clinical Care for Childhood Cancer Survivors*, Cancers, 15 (4) (2023), pp. 1024.
18. J. Huang, S.C. Chan, C.H. Ngai, V. Lok, L. Zhang, D.E.L. Prisno III, W. Xu, Z.J. Zheng, E. Elcarte, M. Withers and et al., *Global incidence, mortality and temporal trends of cancer in children: A joinpoint regression analysis*, Cancer Med., 12 (2) (2023), pp. 1903-1911.
19. M.M. Hudson, D.A. Mulrooney, D.C. Bowers, C.A. Sklar, D.M. Green, S.S. Donaldson, K.C. Oeffinger, J.P. Neglia, A.T. Meadows and L.L. Robison, *High-risk populations identified in Childhood Cancer Survivor Study investigations: implications for risk-based surveillance*, J. Clin. Oncol., 27 (14) (2009), pp. 2405-2414.

20. C.L. Hwang, Y.J. Lai and T.Y. Liu, *A new approach for multiple objective decision making*, Comput. Oper. Res., 20 (8) (1993), pp. 889-899.
21. A. Hüls, S. Van Cor, G. M. Christensen, Z. Li, Y. Liu, L. Shi, J.L. Pearce, R. Bayakly, T.L. Lash, K. Ward and et al., *Environmental, social and behavioral risk factors in association with spatial clustering of childhood cancer incidence*, Spat. Spatiotemporal Epidemiol., 45 (2023), pp. 100582.
22. N.C. Institute, *Leukemia types of cancer*, 2024, Available at: `https://www.cancer.gov/types/leukemia`.
23. V. Keršuliene, E.K. Zavadskas and Z. Turskis, *Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA)*, J. Bus. Econ. Manag., 11 (2) (2010), pp. 243-258.
24. M.K. Ghorabaee, M. Amiri, E.K. Zavadskas, Z. Turskis and J. Antucheviciene, *Determination of objective weights using a new method based on the removal effects of criteria (MEREC)*, Symmetry, 13 (4) (2021), pp. 525.
25. A.F. Klassen, S.J. Anthony, A. Khan, L. Sung and R. Klaassen, *Identifying determinants of quality of life of children with cancer and childhood cancer survivors: a systematic review*, Support. Care Cancer, 19 (2011), pp. 1275-1287.
26. N. Kumar, A. Patel and J. Mahanta, *K-L divergence-based distance measure for Pythagorean fuzzy sets with various applications*, J. Exp. Theor. Artif. Intell., (2023), pp. 1-21.
27. J. Lemmen, F. Njuguna, S. Verhulst, T.A. Vik, J.C.F. Ket, G. Kaspers and S. Mostert, *Late effects of childhood cancer survivors in Africa: A scoping review*, Crit. Rev. Oncol. Hematol., 185 (2023), pp. 103981.
28. L. Liu, M. Krailo, G.H. Reaman and L. Bernstein, *Childhood cancer patients' access to cooperative group cancer programs: a population-based study*, Cancer Interdiscip. Int. J. Am. Cancer Soc., 97 (5) (2003), pp. 1339-1345.
29. P. Liu, P. Rani and A.R. Mishra, *A novel Pythagorean fuzzy combined compromise solution framework for the assessment of medical waste treatment technology*, J. Clean. Prod., 292 (2021), pp. 126047.
30. A. Maas, H.M. Stam, A. Delden, E.C. Dalen, E. Broeder, W.J.E. Tissing, J.J. Loonen, H.J. H. Pal, A.C.H. Vries, M.M.H. Eibrink and et al., *Positive and negative survivor-specific psychosocial consequences of childhood cancer: the DCCSS-LATER 2 psycho-oncology study*, J. Cancer Surviv., 18 (2024), pp. 1505-1516.

31. J. Mahanta and S. Panda, *Distance measure for Pythagorean fuzzy sets with varied applications*, Neural Comput. Appl., 33 (24) (2021), pp. 17161-17171.
32. E.F.M. Hernández, M.P.R. Díaz and L.A.R. Villamizar, *Clustering of non-leukemia childhood cancer in Colombia: a nationwide study*, F1000Res., 10 (2021).
33. R.W. Miller, J.L. Young Jr and B. Novakovic, *Childhood cancer*, Cancer, 75 (1995), pp. 395-405.
34. M.U. Molla, B.C. Giri and P. Biswas, *Extended PROMETHEE method with Pythagorean fuzzy sets for medical diagnosis problems*, Soft Comput., 25 (2021), pp. 4503-4512.
35. W. Health Organization, *Global report on health equity for persons with disabilities*, 2021, Available at: `https://apps.who.int/iris/handle/10665/347370`.
36. The Global Initiative for Childhood Cancer, *The global initiative for childhood cancer*, 2024, Available at: `https://www.who.int/initiatives/the-global-initiative-for-childhood-cancer`.
37. İ. Otay, S. Çevik Onar, B. Öztayşi and C. Kahraman, *Evaluation of sustainable energy systems in smart cities using a Multi-Expert Pythagorean fuzzy BWM & TOPSIS methodology*, Expert Syst. Appl., 250 (2024), pp. 123874.
38. B. Pandey and M.K. Khurana, *An integrated Pythagorean fuzzy SWARA-COPRAS framework to prioritise the solutions for mitigating Industry 4.0 risks*, Expert Syst. Appl., (2024), pp. 124412.
39. D.M. Parkin, C.A. Stiller, G.J. Draper and C.A. Bieber, *The international incidence of childhood cancer*, Int. J. Cancer, 42 (4) (1988), pp. 511-520.
40. P. Rani, A.R. Mishra, R. Krishankumar, K.S. Ravichandran and A.H. Gandomi, *A new Pythagorean fuzzy based decision framework for assessing healthcare waste treatment*, IEEE Trans. Eng. Manag., 69 (6) (2020), pp. 2915-2929.
41. P. Rani, A.R. Mishra, A. Mardani, F. Cavallaro, D. Štreimikienė and S.A.R. Khan, *Pythagorean fuzzy SWARA-VIKOR framework for performance evaluation of solar panel selection*, Sustainability, 12 (10) (2020), pp. 4278.
42. L.A. Rodriguez-Villamizar, M.P. Rojas Díaz, L.A. Acuña Merchán, F.E. Moreno-Corzo and P. Ramírez-Barbosa, *Space-time clustering of childhood leukemia in Colombia: a nationwide study*, BMC Cancer, 20 (1) (2020), pp. 1-10.
43. M.K. Saraji, A. Mardani, M. Köppen, A.R. Mishra and P. Rani, *An extended hesitant fuzzy set using SWARA-MULTIMOORA approach to adapt online education for the control of the pandemic spread of*

COVID-19 in higher education institutions, Artif. Intell. Rev., 55 (1) (2022), pp. 181-206.
44. K. Sathishkumar, M. Chaturvedi, P. Das, S. Stephen and P. Mathur, *Cancer incidence estimates for 2022 & projection for 2025: result from National Cancer Registry Programme, India*, Indian J. Med. Res., 156 (2023), pp. 598-607.
45. American Cancer Society, *Types of childhood cancers*, 2024, Available at: `https://www.cancer.org/cancer/types/cancer-in-children/types-of-childhood-cancers.html`.
46. L.G. Spector, N. Pankratz and E.L. Marcotte, *Genetic and non-genetic risk factors for childhood cancer*, Pediatr. Clin. North Am., 62 (1) (2015), pp. 11-25.
47. P. Thakur, B. Paradowski, N. Gandotra, P. Thakur, N. Saini and W. Sałabun, *A Study and Application Analysis Exploring Pythagorean Fuzzy Set Distance Metrics in Decision Making*, Inform., 15 (1) (2024), pp. 28.
48. M. Torabi and R.J. Rosychuk, *An examination of five spatial disease clustering methodologies for the identification of childhood cancer clusters in Alberta, Canada*, Spatial Spatio-Temporal Epidemiol., 2 (4) (2011), pp. 321-330.
49. M. van Gorp, M.H. Joosten, A. Maas, B.L. Drenth, A. van der Aa-van Delden, L.C. M. Kremer, E. van Dulmen-den Broeder, W.J.E. Tissing, J.J. Loonen, H.J.H. vander Pal and et al., *Psychosocial functioning of parents of dutch long-term survivors of childhood cancer*, Psychosoc. Oncol., 32 (2) (2023), pp. 283-294.
50. F. Xiao and W. Ding, *Divergence measure of Pythagorean fuzzy sets and its application in medical diagnosis*, Appl. Soft Comput., 79 (2019), pp. 254-267.
51. R.R. Yager, *Pythagorean fuzzy subsets*, in: Proc. 2013 Joint IFSA World Congr. and NAFIPS Annu. Meet., IEEE, 2013, pp. 57-61.
52. L.A. Zadeh, *Fuzzy sets*, Inf. Control, 8 (3) (1965), pp. 338-353.
53. E.K. Zavadskas and V. Podvezko, *Integrated determination of objective criteria weights in mcdm*, Int. J. Inf. Technol. Decis. Mak., 15 (2) (2016), pp. 267-283.
54. Q. Zhang, J. Hu, J. Feng, A. Liu and Y. Li, *New similarity measures of Pythagorean fuzzy sets and their applications*, IEEE Access, 7 (2019), pp. 138192-138202.
55. X. Zhang and Z. Xu, *Extension of TOPSIS to multiple criteria decision making with Pythagorean fuzzy sets*, Int. J. Intell. Syst., 29 (12) (2014), pp. 1061-1078.
56. Q. Zhou, H. Mo and Y. Deng, *A new divergence measure of Pythagorean fuzzy sets based on belief function and its application*

in medical diagnosis, Mat., 8 (1) (2020), pp. 142.

---

[1] Department of Mathematics, NIT Silchar, Cachar, Assam, 788010, India.
Email address: naveen_rs@math.nits.ac.in

[2] Department of Mathematics, NIT Silchar, Cachar, Assam, 788010, India.
Email address: juthika@math.nits.ac.in