Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 45 (2024), No. 8, pp. 2107–2128
DOI : 10.47974/JIOS-1766

Ensuring efficient health care delivery : Addressing uncertainties through mixed-constraints fractional transportation

Vishwas Deep Joshi *
Priya Agarwal †
Department of Mathematics
Faculty of Science
JECRC University
Jaipur 303905
Rajasthan
India

Huda Alsaud §
Department of Mathematics
College of Science
King Saud University
P.O. Box-22452
Riyadh 11495
Saudi Arabia

Abstract

Healthcare requires efficient delivery of supplies, but things often change unexpectedly. In the field of healthcare logistics, transportation efficiency plays a fateful role in ensuring the timely delivery of medical supplies, equipment, and personnel. However, the dynamic nature of the healthcare environment brings complexities, such as unexpected changes in demand, transportation disruptions, and differing priorities. This research highlights a novel approach to address these challenges through an innovative model designed for uncertain multi-objective fractional transportation problems with mixed constraints (UMOFTPMC), which aims to address the complexities of healthcare logistics and resource allocation has to be optimized. By integrating uncertain parameters and multiple objectives – such as minimizing transportation costs, maximizing service quality, and ensuring timely delivery – the proposed model provides a comprehensive approach to healthcare transportation management. Through a series of computational experiments and case studies, the efficacy of the mixed-constraint UMOFTPMC model in healthcare logistics is demonstrated by

* *E-mail:* **vdjoshi.or@gmail.com (Corresponding Author)**
† *E-mail:* **priyaagarwal4698@gmail.com**
§ *E-mail:* **halsaud@ksu.edu.sa**

providing robust, efficient, and adaptable transportation solutions according to the unique demands and uncertainties underlying healthcare systems and exhibiting its ability to bring revolution. Using advanced computational methods and analyzing real-world scenarios, the study elucidates the complexities of healthcare transportation and proposes strategies to increase efficiency, adaptability, and flexibility in healthcare supply chain operations.

Subject Classification: *90C29, 90C32, 90C15, 90B90, 90B50, 90B06.*

Keywords: *Healthcare logistics, Uncertain multi-objective fractional transportation problems (UMOFTP), Mixed constraints, Supply chain management, Optimization, Cost minimization, Delivery time optimization, Service quality, Adaptability, Flexibility, Computational methods, Real-world scenarios.*

1. Introduction

The Multi-Objective Fractional Transportation Problems (MOFTPs) extend the classical transportation problem by introducing multiple conflicting objectives that require simultaneous optimization. In this problem, various criteria such as minimizing transportation cost, maximizing customer satisfaction, or minimizing transportation time are considered objectives. Joshi et al [1] present an improved solution approach for multi-objective linear and linear fractional transportation problems solving optimization challenges. Joshi et al [2] have presented a new solution procedure for multi-objective linear fractional transportation problems considering coarse parameters, which contributes to robust optimization methods. The decision variables represent the fraction of goods delivered from each supplier to each destination, subject to supply and demand constraints. Mathematical formulation involves expressing these multiple objectives within a unified optimization model, often employing linear programming or nonlinear programming techniques. MOFTPs provide decision support by offering a range of solutions that allow decision-makers (DMs) to make informed choices when considering trade-offs between conflicting objectives. The MOFTPs extends the classical transportation problem by introducing multiple conflicting objectives that require simultaneous optimization.

Uncertain multi-objective transportation problems (UMOTPs) introduce a layer of complexity by involving uncertainties in the traditional MOTP framework MOTP framework (Fig. 1). Nomani et al [3] proposed a novel approach to solving multi-objective transportation problems, combining a diverse toolkit of optimization methods. Javed et al [4] present a model providing a comprehensive approach addressing uncertain multi-objective transportation problems with all partial objectives. Majumdar [5] and others investigate the uncertain multi-objective Chinese postman problem, highlighting the complexities in optimizing routes. Uddin et al [6] present a goal programming approach to address uncertain multi-objective transportation problems using fuzzy linear membership functions. In these problems, DMs face the challenge of optimizing the transportation of goods between suppliers and destinations while struggling with uncertain parameters such as inconsistency in demand, unexpected transportation costs, or variations in resource availability. Unlike deterministic scenarios, UMOTP requires DMs to consider a range of possible outcomes, making the optimization process inherently more complex. Stochastic modeling techniques, including stochastic programming and chance-constrained programming, are often employed to address uncertainties. Scenario-based approaches enable DMs to explore diverse realizations of uncertain parameters, revealing the robustness of transportation strategies in different scenarios. The goal of robust optimization strategies is to identify solutions that perform well under potential uncertainties. Navigating the UMOTP requires a delicate balance between achieving multiple objectives and managing the uncertainties inherent in the transportation system, providing DMs with a comprehensive approach to address the challenges of dynamic and unpredictable real-world scenarios. Joshi et.al [7] use a goal programming approach to solve linear transportation problems with multiple objectives, which provides a systematic decision-making strategy. Joshi et al [8] investigate the application of neutrosophic environments in solving multi-objective linear fractional transportation problems that contribute to uncertainty modeling. Joshi et.al [9] explores fuzzy transportation planning using a goal programming strategy for uncertainty and multi-objective decision-making.

In our proposed model, we tackle the challenges posed by UMOFTPs within healthcare logistics. Complexity is addressed by incorporating a mixture of constraints, reflecting the complex nature of the healthcare supply chain. Mondal et al [10] focus on solving transportation problems with mixed constraints, providing insights into tackling various optimization challenges. Gupta et al [11] explore a multi-objective capacitated transportation problem with mixed constraints, which contributes to the understanding of optimization in deterministic and uncertain environments. Agarwal et al [12] introduced a shootout method for time-minimized transportation problems with mixed constraints, offering a practical solution for time-sensitive logistics scenarios. Additionally, our model introduces a weighting factor into the symphony of our solutions. We combine our model with a detailed understanding of preferences and increase the accuracy and relevance of the optimization process. This innovative approach is specifically designed to address the unique demands of healthcare, aiming to optimize costs, reduce delivery times, and enhance overall service quality. Think of our model as a virtuoso that easily adjusts the variables of cost, delivery time, and service quality to create a tune that resonates specifically in the healthcare sector. By considering uncertainties and incorporating weight parameters, our model contributes to the efficient and flexible management of healthcare logistics, ensuring timely and effective delivery of essential supplies within the healthcare sector. Imagine a busy healthcare network, where demand for medical supplies ranging from critical medicines to life-saving equipment is constantly fluctuating. Our model steps into this dynamic domain, designed to optimize the transportation of these critical resources through UMOFTPs with mixed constraints. Think of a hospital as a central hub, surrounded by various suppliers and clinics. The challenge lies in considering factors such as allocating resources efficiently, reducing transportation costs, ensuring timely delivery, and maintaining the highest standards of service quality. This complex dance of logistics is where our model excels. Our model acts as a logistics maestro, harmonizing these ideas to create an optimized transportation plan. It adapts to uncertainties such as sudden changes in demand, road closures, or unexpected delays, ensuring that the healthcare supply chain operates not only with efficiency but with subtle reactions to the constantly changing needs of patients and medical facilities. It is dynamic operates simultaneously. In short, it turns the logical puzzle of healthcare delivery into a well-organized symphony, ensuring that each one plays a vital role in the health and well-being of the community.

- **Dynamic Healthcare Landscape:**
  Healthcare logistics resembles a bustling metropolis with varying demands for medical supplies and the challenge lies in streamlining the movement of essential commodities amid uncertainties.
- **Model as Logistic Virtuoso:**
  Our model acts as an expert in solving the complexities of uncertain multi-objective partial transportation problems with mixed constraints. Hospitals, suppliers, and clinics become integral parts of this grand healthcare structure.
- **Optimization of essential activities:**
  The primary objective is to optimize the transportation of medical essential goods such as pharmaceuticals, equipment, and supplies and the key is to balance cost efficiency, on-time delivery, and superior service quality.
- **Conductor Rod: Weight Parameter:**
  The weight parameter acts as a conductor's baton, giving prominence to each note in the healthcare symphony. Urgent medicines and cost-effective transportation are given importance dynamically depending on the priorities.
- **Master of Compatibility:**
  This model dynamically adapts to unpredictable circumstances, just as a musical maestro improvises in response to changing rhythms. Sudden demand surges, unexpected changes, or urgent delivery requirements are addressed with flexibility.
- **Symphony of Efficiency:**
  Beyond solving logistical challenges, the model creates a masterpiece that transforms healthcare supply chain delivery into a harmonious and responsive symphony. The commitment is reflected in Symphony's efficiency, adaptability, and sensitivity to the growing needs of the healthcare ecosystem.

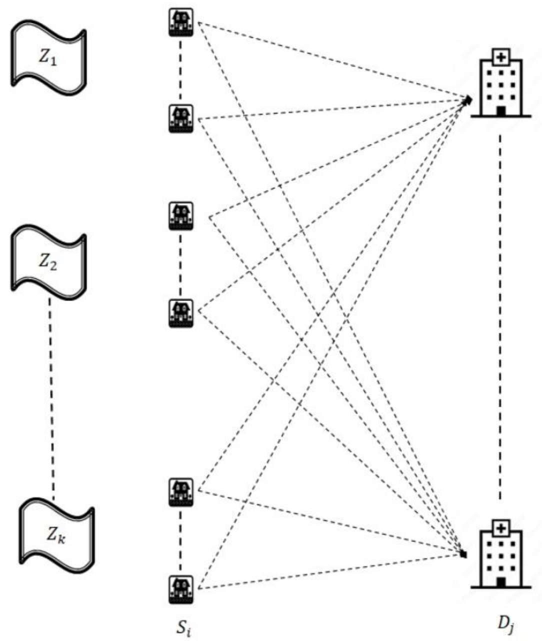

Figure 1
Representation of multi-objective transportation problem

2. Interpretation

2.1 *Uncertain Variable*

An uncertain variable is an ideological tool employed in probability theory and statistical modeling to represent a quantity whose crisp value is not known or estimated. Liu [13] pioneering work introduced the concept of uncertainty theory, which laid the groundwork for dealing with uncertainty in various fields. Further exploration by Liu [14], expanding the discussion to ambiguous processes, hybrid processes, and uncertain processes, also broadens the understanding of uncertainty. In the context of health care, uncertain variables play an important role in capturing the implicit commutability and uncertainty associated with various aspects of the medical field. For example, many factors influence patient outcomes, and their exact trajectories are often uncertain. Clinical parameters, disease progression, and response to treatment can be modeled as uncertain variables due to the implicit commutability observed in individual patient cases. Furthermore, in healthcare decision-making, uncertainties regarding treatment effectiveness, patient compliance, and occurrence of side effects are important considerations. Uncertain variables come into play when assessing the potential outcomes and risks associated with various therapeutic interventions. For example, the recovery period, success rate of surgery, or probability of complications can be modeled as uncertain variables in healthcare scenarios. By incorporating uncertainty into healthcare models, practitioners can increase the robustness of decision-making processes, manage risks more effectively, and develop strategies that account for the dynamic and unpredictable nature of healthcare. Thus, the use of uncertain variables in healthcare settings contributes to a more holistic and adaptive approach to medical decision-making and systems management.

2.2 *Uncertain Distribution*

Continuing Liu [15] contributions, this work highlights the theory and practical applications of uncertain programming, providing insight into implementation challenges and solutions. In the field of health care, the introduction of the uncertain variable τ and its associated uncertainty distribution Δ with the measurement function φ has important implications. This conceptual framework becomes particularly relevant when applied to various aspects of healthcare decision-making and patient outcomes. For example, in clinical scenarios, the uncertain variable τ may represent a patient's response to a particular treatment or the progression of a medical condition. The uncertainty distribution Δ will then capture the range of possible outcomes, specifying probabilities for different health conditions or treatment responses. The measurement function φ becomes an important tool for healthcare professionals to assess the degree of uncertainty surrounding a patient's health status or the effectiveness of interference. Furthermore, the notation $\tau < x$ has a meaningful explanation in healthcare contexts, denoting instances where the uncertainty associated with a variable (e.g., patient recovery time, treatment efficacy) is less than a specified threshold x. This concept may be helpful in risk assessment, treatment planning, and healthcare resource allocation, allowing a nuanced understanding of uncertain variables within the complex landscape of medical decision-making.

Uddin et al [6] present a goal programming approach to address uncertain multi-objective transportation problems using fuzzy linear membership functions. The inverse measurement theorem stands as a fundamental motion in dealing with measures of uncertainty in the context of health care and other fields. The inverse mapping which denoted by Δ^{-1}, for a given value y, provides the basic probabilistic information associated with the uncertainty measure. In simple terms, $\Delta^{-1}(y)$ allows the reflow of exact values from the uncertain domain. For example, If $\Delta(x)$ represents the cumulative distribution function that represents the probability that an uncertain variable τ is less than or equal to x. $(\varphi(\tau < x))$, if $(\varphi(\tau > x))$ can be expressed as $1 - \Delta(x)$. This relation provides a practical way to understand the uncertainty associated with large values of x, complementing our understanding of the uncertain variable. We find crisp value of uncertain parameters by this:

$$\Delta^{-1}(x) = e + \frac{\sqrt{3\sigma}}{\pi} ln\left(\frac{\theta}{1-\theta}\right)$$

3. Symbolism

- X_{ij}: Fraction of goods transported from origin i^{th} to destination j^{th}
- C_{ij}: Unit actual transportation factor (cost, time,…) from origin i^{th} to destination j^{th}
- D_{ij} : Unit standard transportation factor (cost, time,…) from origin i^{th} to destination j^{th}
- a_i: Supply parameters representing the capacity of the source i^{th} $(i = 1,2 \dots m)$
- b_j: Demand parameters representing the amount required at destination $j^{th}(j = 1,2 \dots n)$
- S_i: Available supply at source i^{th}
- D_j: Demand at j^{th} detination
- τ: Uncertain variables affecting the transportation problem
- Δ: Represents the uncertain distribution of the uncertain variable τ
- φ: Uncertain measurement function affects the distribution of uncertainties
- e: Expected value, representing the mean of the distribution
- σ: Standard deviation, measuring the spread of a distribution
- θ: Confidence level, indicating the probability that the uncertain variable falls within a certain range
- δ: The DMs satisfaction level, reflecting subjective satisfaction with the solution
- μ: The normal deviation variable is used to evaluate deviation for all purposes
- I^*: Represents the ideal objective, optimal value
- L_k: Lower bound of the k^{th} objective
- U_k: Upper bound of the k^{th} objective
- W_k: The weight assigned to the k^{th} objective, influencing its importance in the overall optimization $(k = 1,2 \dots K)$.
- Δ^{-1}: Inverse uncertain normal distribution, used in uncertainty quantification

4. Mathematical Model

In this world of optimization, UMOFTP has become a complex puzzle where the uncertainties of supplier, destination, and uncertainty come together. Depict the decision variables X_{ij} as magical pieces representing the transportation of goods between suppliers i and destinations j, with each variable approximate a piece of a magical tapestry. In this scenario, two conflicting objectives weave their threads into the construction of the problem. One objective incarnated by C_{ij} is to minimize total transportation costs.

Second, D_{ij} is to maximize customer satisfaction. However, these objectives are not static; they waver in the presence of uncertainty, and their capacity is affected by different scenarios.

UMOFTP Model:

Minimize $$Z = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}X_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n} D_{ij}X_{ij}}$$

Subject to: $$\sum_{j=1}^{n} X_{ij} \leq a_i$$

$$\sum_{i=1}^{m} X_{ij} \geq b_j$$

$$\forall X_{ij} \geq 0$$

$$\forall\, i = 1,2 \dots m \text{ and } j = 1,2 \dots n$$

Solving the UMOFTP involves employing uncertainty-conscious optimization techniques, such as stochastic programming or robust optimization. One can use a scenario-based approach, where the optimization problem is solved for each scenario, or robust optimization methods can be used that consider a range of possible realizations for uncertain parameters. The resulting solutions will provide DMs with a set of trade-off solutions on the Pareto front, allowing them to make informed decisions considering both objectives and uncertainties. Specific implementation may vary depending on the nature of uncertainties and the preferences of DMs.

The uncertain multi-objective transportation problem with mixed constraints (UMOTPMC) introduces complexity from uncertain factors, conflicting goals, and a mixture of continuous and discrete decision elements. In simple terms, it is like solving a puzzle where the path and cost are uncertain, the goals are contradictory, and some options are complete, while others are like puzzle pieces. DMs balance all these aspects to find the optimal solution in a challenging and dynamic transportation landscape.

UMOTPMC Model:

Minimize $$Z = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}X_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n} D_{ij}X_{ij}}$$

Subject to: $$\sum_{j=1}^{n} X_{ij}\ (\geq/\leq/=) a_i$$

$$\sum_{i=1}^{m} X_{ij} (\geq/\leq/=)\, b_j$$

$$\forall X_{ij} \geq 0$$

$$\forall\, i = 1,2 \dots m \text{ and } j = 1,2 \dots n$$

UMOTPMC has practical significance across a spectrum of real-world applications. In supply chain management, it helps to optimize the transportation of goods between uncertainties in demand, instability in transportation costs, and varying inventory levels. Manufacturers can use UMOTPMC to make informed decisions regarding the transportation of raw materials and finished products through dynamic scenarios. The healthcare sector benefits from its application during critical situations, ensuring efficient delivery of medical supplies. In emergency response scenarios such as natural disasters, UMOTPMC contributes to planning effective transportation routes for timely relief efforts. Additionally, its application extends to environmental impact assessments, urban logistics planning, and military logistics, providing DMs with a versatile tool to optimize transportation strategies considering mixed constraints and conflicting objectives. UMOTPMC emerges as a valuable asset for DMs across various industries, providing a holistic approach to address the complex challenges of uncertain and dynamic transportation scenarios.

Our proposed model presents a new approach to problem-solving known as the UMOTPMC. This innovative framework modulates the complexities of dealing with uncertainties, inconsistent objectives, and a mix of continuous and discrete decision elements. To deal with these complexities, we give importance to the various factors involved. These weights act as a guiding force, influencing the optimization process by assigning priorities to different objectives and constraints. By introducing this weighting dimension, our model aims to provide DMs with a flexible and tailored tool to address the unique challenges posed by scenarios with uncertain and mixed constraints, allowing a more nuanced and personalized optimization strategy. And the UMOTPMC, we go a step further by incorporating patient satisfaction levels into the optimization framework. This recognizes the importance of additional customer experience, particularly in the context of healthcare logistics.

Proposed Model:

Maximize $$Z = \sum_{k=1}^{K} \frac{\delta}{\mu(1-W_k)}$$

Subject to: $$Z = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}X_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n} D_{ij}X_{ij}} \leq U_k(1-\delta) + L_k\delta$$

$$Z = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}X_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n} D_{ij}X_{ij}} \leq I^* + \mu(1-W_k)$$

$$\sum_{j=1}^{n} X_{ij} \ (\geq/\leq/=)\ a_i$$

$$\sum_{i=1}^{m} X_{ij} (\geq/\leq/=)\ b_j$$

$$\forall X_{ij} \geq 0\ ,\ 0 \leq \delta \leq 1, \mu \geq 0$$

$$\sum_{k=1}^{K} W_k = 1, 0 \leq W_k \leq 1$$

$$\forall\ i = 1,2 \ldots m\ , j = 1,2 \ldots n, k = 1,2 \ldots K$$

$$\sum_{i=1}^{m} a_i = \sum_{j=1}^{n} b_j$$

As we navigate uncertainties, mixed constraints, and conflicting objectives, the inclusion of patient satisfaction metrics underscores our commitment to providing not only efficient but patient-centric transportation solutions. By giving due importance to this satisfaction level within our model, we provide

DMs with a comprehensive tool that not only optimizes logistics under uncertainty but also prioritizes the well-being and satisfaction of end users. This patient-centered dimension aims to enhance the overall quality of healthcare transportation services, aligning our model with a holistic and human-centered approach. The integration of the raking approach with TOPSIS (Technique of Preference Order by Similarity to Ideal Solution) provides a strategic framework for multi-criteria decision-making. Chakraborty [16] conducts a comparative analysis of TOPSIS and modified TOPSIS methods, which provide insights into decision-making practices.

TOPSIS calculates the proximity of each alternative to the optimal solution P^+ and negative optimal solutions P^-, providing a comprehensive assessment. The final step involves ranking the options based on their TOPSIS scores and articulating the preferred solutions in the decision context. In this paper, we make an in-depth comparison between our innovative approach and established approaches of the past. Additionally, we present an optimal solution to assess and point out the superior aspects of our proposed method. The purpose of this comprehensive analysis is to illustrate the strengths and benefits of our approach in the given context.

$$Rank = \frac{P^-}{P^- + P^+}$$

5. The proposed solution process

The suggested method is methodically described in the solution process shown in Fig. 2, which offers a clear framework for dealing with the problem at present.

Step 1: Specify uncertain parameters: Use the normal distribution to determine specific values for uncertain parameters. Select the expected value (e) and standard deviation (σ). The DMs chooses a confidence level (θ) to define the range of uncertainties.

Step 2: Formulate a MOFTP using the categorical values obtained from Step 1.

Step 3: Consider MOFTP as a single objective problem and find the optimal value.

Step 4: Allocate particular weights to each objective based on their importance, reflecting the priorities of the DMs.

Step 5: Submit solution for DM: Show potential solutions to DMs. If satisfaction is achieved, proceed to step 6. If not, revisit Steps 1 through 4, address concerns, and refine objectives until a compromise solution is reached.

Step 6: Evaluate solutions using TOPSIS. Evaluate and rank solutions, providing a structured list of the best options for transportation problems

Step 7: Stop

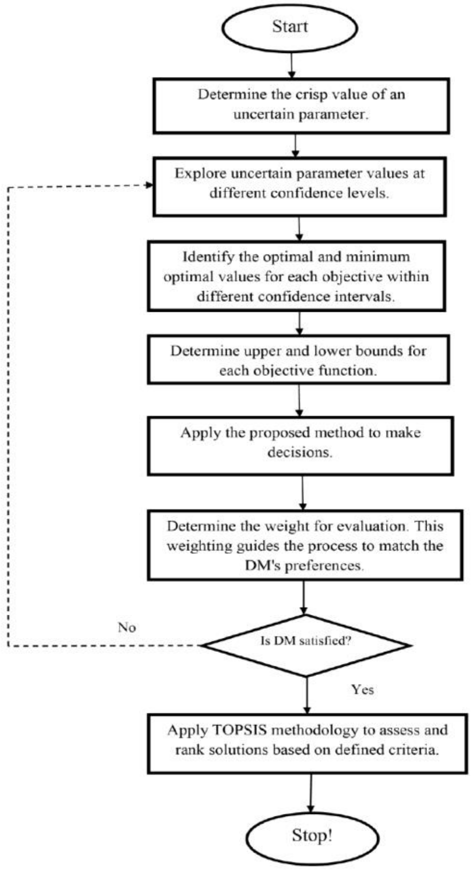

Figure 2

This flow chart represents of the proposed model

6. Illustrative Example

The purpose of this healthcare transportation optimization is to efficiently distribute medical supplies amid uncertain demand, minimize costs, and maximize coverage. The first objective $Z_1 = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}^{1}}{\sum_{i=1}^{m}\sum_{j=1}^{n} D_{ij}^{1}}$ focuses on minimizing the overall transportation expenditure while keeping the unit cost in mind. Additionally, the second objective $Z_2 = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}^{2}}{\sum_{i=1}^{m}\sum_{j=1}^{n} D_{ij}^{2}}$ addresses demand uncertainty intending to maximize coverage of medical supplies across all facilities. Constraints ensure that supply capacities are not exceeded, demands are met and the quantity transported remains non-negative. This structured approach balances cost-effectiveness and coverage, provides a systematic solution to stakeholders' input-specific parameters, and achieves an optimal transportation plan that aligns with healthcare goals. Accommodate three suppliers (sources S_1, S_2, S_3) and four health facilities (destinations D_1, D_2, D_3, D_4).

Table 1
Data of uncertain transportation actual cost C_{ij}^1

	D_1	D_2	D_3	D_4
S_1	(10,0.1)	(20,0.1)	(15,0)	(24,0.1)
S_2	(22,0)	(18,0.1)	(24,0)	(23,0.15)
S_3	(20,0.1)	(12,0.2)	(22,0.1)	(13,0)

Table 2
Data of uncertain transportation standard cost D_{ij}^1

	D_1	D_2	D_3	D_4
S_1	(3,0.1)	(3,1)	(2.5,0.1)	(5,2)
S_2	(4,0)	(4,1.5)	(4,0)	(4,0.1)
S_3	(3,0)	(4,1)	(4,1)	(5,1.5)

Table 3
Data of uncertain transportation actual time C_{ij}^2

	D_1	D_2	D_3	D_4
S_1	(6,1.5)	(4,1)	(8,2)	(9,1)
S_2	(5,1.5)	(6,1)	(4,1)	(4,1.5)
S_3	(8,1.5)	(3,1)	(2.5,0.1)	(5,1)

Table 4
Data of uncertain transportation standard time D_{ij}^2

	D_1	D_2	D_3	D_4
S_1	(3,0.5)	(2.5,1)	(5,1)	(6,1)
S_2	(5,2)	(4,0)	(6,1)	(3,1)
S_3	(5,1.5)	(4,1)	(9,1)	(9,1)

Table 5
Data of uncertain demand

b_1	b_2	b_3	b_4
(40,3)	(36,4)	(35,5)	(40,3)

Table 6
Data of uncertain supply

a_1	a_2	a_3
(55,4)	(60,5)	(70,4)

Continuing this analytical process, we are using 0.55 confidence level for data given in table 1-6. For crisp values for the proposed example refer Tables 7-12.

Table 7

Data of crisp value for transportation actual cost C_{ij}^1

	D_1	D_2	D_3	D_4
S_1	10.01	20.01	15	24.01
S_2	22	18.01	24	23.01
S_3	20.01	12.02	22.01	13

Table 8

Data of crisp value for transportation standard cost D_{ij}^1

	D_1	D_2	D_3	D_4
S_1	3.01	3.11	2.51	5.22
S_2	4	4.16	4	4.01
S_3	3	4.11	4.11	5.16

Table 9

Data of crisp value for transportation actual time C_{ij}^2

	D_1	D_2	D_3	D_4
S_1	6.16	4.11	8.22	9.11
S_2	5.16	6.11	4.11	4.16
S_3	8.16	3.11	2.51	5.11

Table 10

Data of crisp value for transportation standard time D_{ij}^2

	D_1	D_2	D_3	D_4
S_1	3.05	2.61	5.11	6.11
S_2	5.22	4	6.11	3.11
S_3	5.16	4.11	9.11	9.11

Table 11

Data of crisp value for demand

b_1	b_2	b_3	b_4
40.33	36.44	35.55	40.33

Table 12

Data of crisp value for supply

a_1	a_2	a_3
55.44	60.55	70.44

By removing the uncertainties inherent in medical research, our method becomes a strategic tool within the 55% confidence spectrum. As we traverse this healthcare arena, the application of our optimized technology emerges as an important guide, revealing a unique value that addresses the complexities of our healthcare inquiry and this defined confidence interval.

$$\text{Maximize } Z = \sum_{k=1}^{K} \frac{\delta}{\mu(1-W_k)}$$

Subject to:

$$\frac{10.01x_{11}+20.01x_{12}+15x_{13}+24.01x_{14}+22x_{21}+18.01x_{22}+24x_{23}+23.01x_{24}+20.01x_{31}+12.02x_{32}+22.01x_{33}+13x_{34}}{3.01x_{11}+3.11x_{12}+2.51x_{13}+5.22x_{14}+4x_{21}+4.16x_{22}+4x_{23}+4.01x_{24}+3x_{31}+4.11x_{32}+4.11x_{33}+5.16x_{34}} +(4.810676-3.188854)\delta \le 4.810676$$

$$\frac{6.16x_{11}+4.11x_{12}+8.22x_{13}+9.11x_{14}+5.16x_{21}+6.11x_{22}+4.11x_{23}+4.16x_{24}+8.16x_{31}+3.11x_{32}+2.51x_{33}+5.11x_{34}}{3.05x_{11}+2.61x_{12}+5.11x_{13}+6.11x_{14}+5.22x_{21}+4x_{22}+6.11x_{23}+3.11x_{24}+5.16x_{31}+4.11x_{32}+9.11x_{33}+9.11x_{34}} +(1.084752-0.672042)\delta \le 1.084752$$

$$\frac{10.01x_{11}+20.01x_{12}+15x_{13}+24.01x_{14}+22x_{21}+18.01x_{22}+24x_{23}+23.01x_{24}+20.01x_{31}+12.02x_{32}+22.01x_{33}+13x_{34}}{3.01x_{11}+3.11x_{12}+2.51x_{13}+5.22x_{14}+4x_{21}+4.16x_{22}+4x_{23}+4.01x_{24}+3x_{31}+4.11x_{32}+4.11x_{33}+5.16x_{34}} \le 3.188854+\mu(1-W_k)$$

$$\frac{6.16x_{11}+4.11x_{12}+8.22x_{13}+9.11x_{14}+5.16x_{21}+6.11x_{22}+4.11x_{23}+4.16x_{24}+8.16x_{31}+3.11x_{32}+2.51x_{33}+5.11x_{34}}{3.05x_{11}+2.61x_{12}+5.11x_{13}+6.11x_{14}+5.22x_{21}+4x_{22}+6.11x_{23}+3.11x_{24}+5.16x_{31}+4.11x_{32}+9.11x_{33}+9.11x_{34}} \le 0.672042+\mu(1-W_k)$$

$$\mathrm{x}_{11}+\mathrm{x}_{12}+\mathrm{x}_{13}+\mathrm{x}_{14} \ge 55.44$$
$$\mathrm{x}_{21}+\mathrm{x}_{22}+\mathrm{x}_{23}+\mathrm{x}_{24} = 60.55$$
$$\mathrm{x}_{31}+\mathrm{x}_{32}+\mathrm{x}_{33}+\mathrm{x}_{34} \le 70.44$$
$$\mathrm{x}_{11}+\mathrm{x}_{21}+\mathrm{x}_{31} \ge 40.33$$
$$\mathrm{x}_{12}+\mathrm{x}_{22}+\mathrm{x}_{32} = 36.44$$
$$\mathrm{x}_{13}+\mathrm{x}_{23}+\mathrm{x}_{33} \le 35.55$$
$$\mathrm{x}_{14}+\mathrm{x}_{24}+\mathrm{x}_{34} = 40.33$$
$$\mu \ge 0, 0 \le \delta \le 1, \forall X_{ij} \ge 0, \forall i,j, \sum_{k=1}^{K} W_k = 1, 0 \le W_k \le 1 \ \forall k = 1,2 \ldots K .$$

7. Result and discussions

Using LINGO 18.0, we can solve our proposed method and we get the table 13. Provide a comprehensive framework that deals with uncertainties, includes inconsistent objectives, and prioritizes patient satisfaction; this method equips DMs with valuable insights and optimal solutions.

Table 13
Objectives value for desired goals and rankings based on confidence level

Confidence Level (θ)	Weight (W)	Z_1	Z_2	distances between ideal solution (P^+)	distances between anti-ideal solution (P^-)	Rank in %	Rank
0.55	0.1,0.9	4.043494	0.7665104	0.860157543	4.050397273	82%	2
	0.2,0.8	3.7780456	0.8193539	0.607633308	4.019738095	87%	2
	0.3,0.7	3.6225714	0.8579671	0.472178084	3.999894305	89%	2
	0.4,0.6	3.5190839	0.8921706	0.397135683	3.978379164	91%	2
	0.5,0.5	3.4366533	0.9200284	0.350796887	3.959271253	92%	2
	0.6,0.4	3.3696938	0.943558	0.326402702	3.940773437	92%	2
	0.7,0.3	3.3202857	0.9791145	0.3341432	3.904392027	92%	2
	0.8,0.2	3.2744818	1.014998	0.353562134	3.865463763	92%	2
	0.9,0.1	3.2308153	1.0504521	0.380766225	3.825556136	91%	2
Proposed Method	—	3.5105694	0.916017	0.404014511	3.953703612	91%	2
Uddin's Method	—	3.7728275	0.8206166	0.602882152	4.019051202	87%	3
Ideal Value	—	3.188854	0.67204	0.000314	4.27835409	100%	1
Worst Value	—	4.810676	1.084752	1.673814923	3.772201583	69%	4
0.6	0.1,0.9	3.972192	0.7691893	0.858207374	3.929720983	82%	2
	0.2,0.8	3.7219169	0.8250752	0.621225609	3.895857861	86%	2
	0.3,0.7	3.5660766	0.869523	0.487573961	3.87060017	89%	2
	0.4,0.6	3.4602081	0.9017198	0.409782247	3.851966807	90%	2
	0.5,0.5	3.3756	0.9309	0.362624869	3.832042783	91%	2
	0.6,0.4	3.3078311	0.9575	0.34013668	3.810356821	92%	2
	0.7,0.3	3.2561275	0.9942398	0.347868601	3.772813151	92%	2
	0.8,0.2	3.2081	1.0303	0.36678882	3.733725303	91%	2
	0.9,0.1	3.1625	1.0653	0.39324769	3.694265444	90%	2
Proposed Method	—	3.4478391	0.92708301	0.414501865	3.826168433	90%	2
Uddin's Method	—	3.6980654	0.8306166	0.599533479	3.89308185	87%	3
Ideal Value	—	3.119231	0.67444	0	4.16470565	100%	1
Worst Value	—	4.6915264	1.098995	1.628606697	3.631359306	69%	4
0.65	0.1,0.9	3.9008	0.7712	0.857664349	3.835284978	82%	2
	0.2,0.8	3.652914	0.8277	0.623139362	3.802042914	86%	2
	0.3,0.7	3.5045	0.8721	0.496255948	3.776695663	88%	2
	0.4,0.6	3.3940586	0.9099	0.417039934	3.75331465	90%	2
	0.5,0.5	3.3111	0.9396	0.371735197	3.732882341	91%	2
	0.6,0.4	3.2447	0.9714	0.354177551	3.705284805	91%	2
	0.7,0.3	3.1907	1.009	0.361572801	3.66696742	91%	2
	0.8,0.2	3.1404	1.0454	0.380090004	3.627557341	91%	2
	0.9,0.1	3.1182152	1.0995	0.428609178	3.564945122	89%	2
Proposed Method	—	3.3841542	0.93842222	0.425785708	3.72366572	90%	2
Uddin's Method	—	3.611661	0.8369426	0.585665295	3.797911731	87%	3
Ideal Value	—	3.0483665	0.6766206	0	4.076504602	100%	1
Worst Value	—	4.5978938	1.114229	1.610135387	3.51878439	69%	4
0.7	0.1,0.9	3.8286	0.7735	0.856384647	3.744033811	81%	2
	0.2,0.8	3.5836	0.8304	0.624780583	3.711678749	86%	2
	0.3,0.7	3.4352	0.8752	0.498039052	3.686905158	88%	2
	0.4,0.6	3.3289	0.9133	0.422408666	3.663233091	90%	2
	0.5,0.5	3.2454	0.9471	0.379067522	3.6387745	91%	2
	0.6,0.4	3.182	0.9858	0.368763553	3.603080184	91%	2
	0.7,0.3	3.1253135	1.0242	0.375564257	3.564110555	90%	2

	0.8,0.2	3.0728	1.0608	0.393556679	3.524544581	90%	2
	0.9,0.1	3.0236	1.0961	0.419676419	3.484612539	89%	2
Proposed Method	—	3.3139348	0.94515556	0.429043417	3.630695894	89%	2
Uddin's Method	—	3.5348851	0.8433741	0.581175025	3.705035842	86%	3
Ideal Value	—	2.9774487	0.6789689	0	3.991869334	100%	1
Worst Value	—	4.5075096	1.1301756	1.595203386	3.409198702	68%	4
0.75	0.1,0.9	3.7549144	0.7756379	0.855866215	3.647448391	81%	2
	0.2,0.8	3.5124045	0.8331678	0.626839265	3.615862037	85%	2
	0.3,0.7	3.3653371	0.878256	0.501426866	3.591643028	88%	2
	0.4,0.6	3.2590421	0.9175904	0.426340493	3.567353642	89%	2
	0.5,0.5	3.1753641	0.9522976	0.383425262	3.542364874	90%	2
	0.6,0.4	3.1127742	0.9939659	0.375942015	3.50332497	90%	2
	0.7,0.3	3.0553875	1.0337627	0.38363962	3.462809908	90%	2
	0.8,0.2	3.0047874	1.0701933	0.401830629	3.423280449	89%	2
	0.9,0.1	2.9518366	1.109739	0.43123422	3.378344931	89%	2
Proposed Method	—	3.2435387	0.9516234	0.43388867	3.532497578	89%	2
Uddin's Method	—	3.4516805	0.8501511	0.572897924	3.607240278	86%	3
Ideal Value	—	2.9042816	0.6811349	0	3.902577445	100%	1
Worst Value	—	4.4114837	1.1465638	1.577428994	3.293227409	68%	4
0.8	0.1,0.9	3.6706967	0.7780369	0.853069205	3.541205999	81%	2
	0.2,0.8	3.4315932	0.8360211	0.627481718	3.510909383	85%	2
	0.3,0.7	3.2850184	0.8818913	0.502819301	3.487132956	87%	2
	0.4,0.6	3.1798395	0.9218936	0.429083125	3.462806361	89%	2
	0.5,0.5	3.0975066	0.95853	0.388446282	3.435984443	90%	2
	0.6,0.4	3.0343607	1.0012452	0.381419765	3.396007216	90%	2
	0.7,0.3	2.9769447	1.0434714	0.39125022	3.352652248	90%	2
	0.8,0.2	2.923054	1.0847226	0.413210831	3.307464223	89%	2
	0.9,0.1	2.8718686	1.1254416	0.444307333	3.260804439	88%	2
Proposed Method	—	3.1634314	0.95902819	0.437863861	3.424653845	89%	2
Uddin's Method	—	3.3581137	0.8578726	0.562849186	3.49987429	86%	3
Ideal Value	—	2.8228433	0.6838473	0	3.804602954	100%	1
Worst Value	—	4.3053954	1.1659301	1.558962654	3.163971706	67%	4
0.81	0.1,0.9	3.6544788	0.7789644	0.85304119	3.520878499	80%	2
	0.2,0.8	3.4161741	0.8371773	0.628279587	3.490813839	85%	2
	0.3,0.7	3.2700067	0.8834656	0.504145591	3.466869066	87%	2
	0.4,0.6	3.1648984	0.9237523	0.430620733	3.442435767	89%	2
	0.5,0.5	3.0828092	0.9611316	0.390661027	3.414868447	90%	2
	0.6,0.4	3.0194204	1.0040079	0.383610049	3.374785654	90%	2
	0.7,0.3	2.9617589	1.0470466	0.394045529	3.330499979	89%	2
	0.8,0.2	2.9076976	1.0890707	0.416695001	3.284369317	89%	2
	0.9,0.1	2.8560914	1.1307898	0.44870867	3.236475867	88%	2
Proposed Method	—	3.1481484	0.9617118	0.439652535	3.403421905	89%	2
Uddin's Method	—	3.3393498	0.8604334	0.560903028	3.479050281	86%	3
Ideal Value	—	2.8066493	0.6848134	0	3.7865678	100%	1
Worst Value	—	4.285337	1.1723163	1.556976683	3.136695951	67%	4
0.82	0.1,0.9	3.6338313	0.7791216	0.852787045	3.496101935	80%	2
	0.2,0.8	3.3959838	0.8374512	0.628496681	3.466252515	85%	2
	0.3,0.7	3.2501788	0.8838216	0.504727721	3.442417806	87%	2
	0.4,0.6	3.1447272	0.923969	0.430814343	3.418376567	89%	2
	0.5,0.5	3.0630168	0.9618384	0.391442295	3.39030952	90%	2
	0.6,0.4	2.9993982	1.0048059	0.384310027	3.350196716	90%	2
	0.7,0.3	2.9418064	1.0482035	0.395094015	3.305479943	89%	2

	0.8,0.2	2.8875566	1.090788	0.418222584	3.258664002	89%	2
	0.9,0.1	2.8360005	1.1328864	0.450620734	3.210265455	88%	2
Proposed Method	—	3.1280555	0.96254284	0.440282249	3.378666802	88%	2
Uddin's Method	—	3.3172405	0.8615889	0.559575994	3.454032876	86%	3
Ideal Value	—	2.786252	0.6850202	0	3.763474094	100%	1
Worst Value	—	4.2603342	1.175103	1.553415425	3.108339082	67%	4
0.83	0.1,0.9	3.6142213	0.7796342	0.852087889	3.468675088	80%	2
	0.2,0.8	3.377145	0.8379943	0.628537081	3.439267922	85%	2
	0.3,0.7	3.2317156	0.8845616	0.505153937	3.415526397	87%	2
	0.4,0.6	3.1258251	0.9248011	0.430882959	3.39171194	89%	2
	0.5,0.5	3.0447917	0.9632669	0.392419091	3.363003708	90%	2
	0.6,0.4	2.9809777	1.0064689	0.385349688	3.322701188	90%	2
	0.7,0.3	2.9235585	1.0503723	0.396663104	3.277366205	89%	2
	0.8,0.2	2.8692219	1.0936653	0.420426246	3.229674086	88%	2
	0.9,0.1	2.8173087	1.1367136	0.453700352	3.180086574	88%	2
Proposed Method	—	3.1094184	0.96416424	0.441058404	3.351073785	88%	2
Uddin's Method	—	3.2956678	0.8609237	0.556623575	3.428974937	86%	3
Ideal Value	—	2.7673185	0.6857757	0	3.738087602	100%	1
Worst Value	—	4.232792	1.1798196	1.546509604	3.074914964	67%	4
0.84	0.1,0.9	3.5937447	0.7805468	0.854171428	3.446427144	80%	2
	0.2,0.8	3.3574397	0.8390442	0.631365464	3.417130335	84%	2
	0.3,0.7	3.2124737	0.8858448	0.508390356	3.393304506	87%	2
	0.4,0.6	3.1083208	0.9246425	0.43456475	3.370946345	89%	2
	0.5,0.5	3.0259309	0.9649494	0.395652833	3.34063605	89%	2
	0.6,0.4	2.9619871	1.0082565	0.388144643	3.300373332	89%	2
	0.7,0.3	2.9044797	1.0527735	0.399498779	3.254432042	89%	2
	0.8,0.2	2.8500084	1.0967324	0.423428624	3.206023711	88%	2
	0.9,0.1	2.7979459	1.1404807	0.456992958	3.155636188	87%	2
Proposed Method	—	3.090259	0.96591898	0.44429141	3.328540395	88%	2
Uddin's Method	—	3.2334194	0.8654751	0.520375226	3.41091427	87%	3
Ideal Value	—	2.7447561	0.6865937	4E-08	3.7182372	100%	1
Worst Value	—	4.2111039	1.1845319	1.54858591	3.048388655	66%	4
0.85	0.1,0.9	3.5742642	0.7808945	0.850361928	3.422824469	80%	2
	0.2,0.8	3.3400095	0.8395963	0.629702668	3.393750029	84%	2
	0.3,0.7	3.1945991	0.8866721	0.506568895	3.370097764	87%	2
	0.4,0.6	3.0885025	0.9269008	0.432199214	3.346747709	89%	2
	0.5,0.5	3.0083618	0.9661988	0.395007752	3.317187903	89%	2
	0.6,0.4	2.9443365	1.0096346	0.387983305	3.276742591	89%	2
	0.7,0.3	2.8867334	1.0548654	0.400379868	3.229853733	89%	2
	0.8,0.2	2.8322117	1.0995145	0.425382489	3.180478175	88%	2
	0.9,0.1	2.779837	1.1441965	0.460186977	3.12882991	87%	2
Proposed Method	—	3.0720951	0.96760817	0.443256348	3.304594684	88%	2
Uddin's Method	—	3.252321	0.8671484	0.55340527	3.380096375	86%	3
Ideal Value	—	2.7291228	0.6868125	0	3.696609245	100%	1
Worst Value	—	4.1869023	1.1892398	1.54193199	3.018339319	66%	4
0.86	0.1,0.9	3.5512591	0.781577	0.849722953	3.393876757	80%	2
	0.2,0.8	3.3168518	0.8402778	0.628895409	3.365462649	84%	2
	0.3,0.7	3.1729415	0.8876109	0.507240993	3.341682358	87%	2
	0.4,0.6	3.0671467	0.9280327	0.433164662	3.318334704	88%	2
	0.5,0.5	2.9866675	0.9676418	0.395853227	3.288651156	89%	2
	0.6,0.4	2.9223653	1.0113413	0.388850697	3.24800511	89%	2
	0.7,0.3	2.8650027	1.0570585	0.401787902	3.200507989	89%	2

	0.8,0.2	2.8103432	1.1025076	0.427496913	3.150138485	88%	2
	0.9,0.1	2.7577806	1.148062	0.463127291	3.097371286	87%	2
Proposed Method	—	3.0500398	0.96934551	0.444018926	3.275633908	88%	2
Uddin's Method	—	3.2271417	0.8693532	0.551184206	3.35084353	86%	3
Ideal Value	—	2.7067315	0.6877568	0	3.669892016	100%	1
Worst Value	—	4.1579314	1.1941506	1.537015234	2.983547015	66%	4
0.87	0.1,0.9	3.529659	0.7821636	0.848933379	3.369436581	80%	2
	0.2,0.8	3.2960669	0.8409754	0.628930917	3.341425633	84%	2
	0.3,0.7	3.1530567	0.8886196	0.508228639	3.317533463	87%	2
	0.4,0.6	3.0473981	0.9294669	0.4344747	3.293942927	88%	2
	0.5,0.5	2.9667906	0.9693793	0.397269847	3.264082075	89%	2
	0.6,0.4	2.9024136	1.0133684	0.390456867	3.223164826	89%	2
	0.7,0.3	2.8449534	1.0598144	0.404004661	3.174805432	89%	2
	0.8,0.2	2.790249	1.1059686	0.430377117	3.123545895	88%	2
	0.9,0.1	2.7373948	1.1524731	0.466890541	3.069574223	87%	2
Proposed Method	—	3.0297758	0.97135881	0.445295984	3.250683308	88%	2
Uddin's Method	—	3.2039032	0.87173742	0.549465497	3.325739129	86%	3
Ideal Value	—	2.6859163	0.6884292	0	3.647786529	100%	1
Worst Value	—	4.1332937	1.1996896	1.535020695	2.952707225	66%	4
0.88	0.1,0.9	3.5158723	0.7805737	0.855519475	3.343046492	80%	2
	0.2,0.8	3.2851933	0.8382309	0.637661787	3.316002382	84%	2
	0.3,0.7	3.14557	0.88538	0.518957551	3.292253085	86%	2
	0.4,0.6	3.041308	0.925328	0.444230398	3.269781073	88%	2
	0.5,0.5	2.9606874	0.963316	0.403268433	3.242739743	89%	2
	0.6,0.4	2.8961969	1.0040471	0.390777047	3.206442024	89%	2
	0.7,0.3	2.8405012	1.049378	0.400904895	3.160025963	89%	2
	0.8,0.2	2.7873338	1.094497	0.423668877	3.11061558	88%	2
	0.9,0.1	2.7360224	1.139862	0.4565872	3.058501268	87%	2
Proposed Method	—	3.0231873	0.96451252	0.451790361	3.229913743	88%	2
Uddin's Method	—	3.1945729	0.8683613	0.558915443	3.300839884	86%	3
Ideal Value	—	2.6652909	0.6887867	0	3.622915425	100%	1
Worst Value	—	4.1052462	1.2055375	1.529870143	2.917790638	66%	4
0.89	0.1,0.9	3.4383068	0.7830549	0.802708337	3.314959528	81%	2
	0.2,0.8	3.2516039	0.842179	0.629328287	3.282573465	84%	2
	0.3,0.7	3.1106221	0.8907757	0.510856738	3.258167254	86%	2
	0.4,0.6	3.0047983	0.9321057	0.437187267	3.234657734	88%	2
	0.5,0.5	2.9236175	0.9721173	0.399595376	3.205140181	89%	2
	0.6,0.4	2.859008	1.0166347	0.393037632	3.163785284	89%	2
	0.7,0.3	2.8017694	1.0646109	0.408032286	3.113563846	88%	2
	0.8,0.2	2.7467732	1.1127735	0.436216532	3.059794967	88%	2
	0.9,0.1	2.6934639	1.161522	0.474862576	3.002949102	86%	2
Proposed Method	—	2.981107	0.97508597	0.444022429	3.191293029	88%	2
Uddin's Method	—	3.1524452	0.8746398	0.543845068	3.267026092	86%	3
Ideal Value	—	2.641062	0.6895596	0	3.593541138	100%	1
Worst Value	—	4.0727058	1.2115526	1.523837479	2.878145146	65%	4
0.9	0.1,0.9	3.4555527	0.7839867	0.846214676	3.276973178	79%	2
	0.2,0.8	3.2253208	0.8432291	0.629601164	3.250301304	84%	2
	0.3,0.7	3.0853597	0.8923616	0.512274072	3.225630422	86%	2
	0.4,0.6	2.9796578	0.9339851	0.438852225	3.202107332	88%	2
	0.5,0.5	2.9016657	0.9856439	0.411748365	3.158840022	88%	2
	0.6,0.4	2.8333301	1.0188528	0.394541611	3.131226729	89%	2
	0.7,0.3	2.7761202	1.067684	0.410300065	3.079970761	88%	2

	0.8,0.2	2.7210467	1.1168268	0.439386295	3.02495631	87%	2
	0.9,0.1	2.66736	1.1668845	0.47925579	2.966430379	86%	2
Proposed Method	—	2.9606015	0.97882828	0.450423553	3.155796308	88%	2
Uddin's Method	—	3.1229709	0.878867	0.542211227	3.232404342	86%	3
Ideal Value	—	2.6145122	0.6905514	0	3.56393604	100%	1
Worst Value	—	4.0397575	1.2183836	1.519845715	2.837433716	65%	4
0.95	0.1,0.9	3.280106	0.7886449	0.838143205	3.070903072	79%	2
	0.2,0.8	3.0648987	0.8505434	0.636816043	3.04463282	83%	2
	0.3,0.7	2.9250333	0.9009587	0.519984636	3.021940242	85%	2
	0.4,0.6	2.8207914	0.9453872	0.449197003	2.997363422	87%	2
	0.5,0.5	2.7348793	0.9839689	0.40702226	2.972138336	88%	2
	0.6,0.4	2.6706531	1.031582	0.403111451	2.927727212	88%	2
	0.7,0.3	2.6141247	1.0861249	0.424245131	2.869384318	87%	2
	0.8,0.2	2.5586042	1.142341	0.459917299	2.805245282	86%	2
	0.9,0.1	2.5031471	1.203084	0.510025253	2.732859571	84%	2
Proposed Method	—	2.7969153	0.992515	0.458492809	2.949485905	87%	2
Uddin's Method	—	2.9354914	0.8966817	0.527974118	3.024131322	85%	3
Ideal Value	—	2.4470822	0.6961496	0	3.379045522	100%	1
Worst Value	—	3.8298763	1.2640038	1.494850466	2.576235989	63%	4

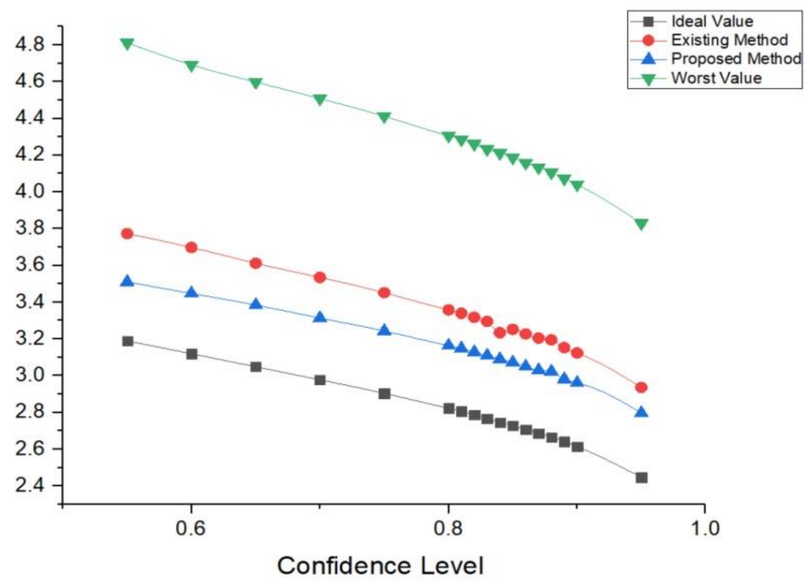

Figure 3
Optimization scenarios: comparative analysis of proposed and existing methods with ideal and worst values

This graph (fig.3) reveals the optimization scenario, displaying the objective values obtained from both the proposed and existing methods compared to ideal and worst-case benchmarks.

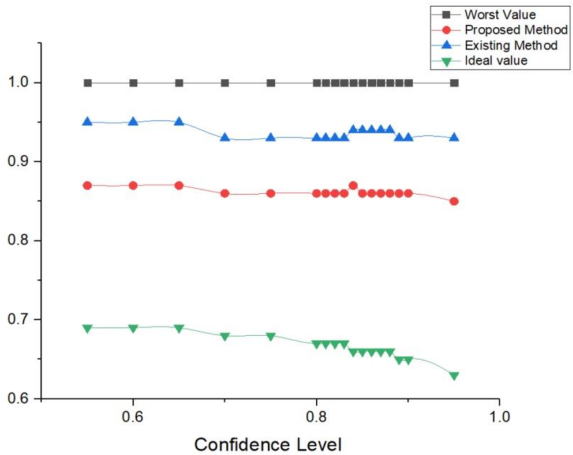

Figure 4
Optimization ranking: nearness to optimal values in proposed and existing methods

The closest of our method to optimal value becomes revealed, giving DMs an expansion of choices. This visual narrative empowers DMs with a rich range of options, facilitating the selection of decisions that align with their goals and aspirations. In the context of healthcare logistics, this graph highlights a compelling narrative that compares the objective values achieved by our proposed method against existing approaches. Positioned alongside ideal and worst-case benchmarks, the graph highlights the optimization journey. Show the closeness of our method to an optimal value, empower healthcare DMs with a spectrum of options, and facilitate the selection of strategies that reconcile accuracy, efficiency, and patient-centered care.

In this ranking graph (fig.4) designed for healthcare DMs, each method's closeness to the optimal value takes center stage. By visualizing the rankings, DMs gain information about which method more closely matches the optimal solution. This graph becomes a compass, guiding healthcare professionals toward options that excel in accuracy, efficiency, and optimal patient outcomes.

8. Conclusion

In the field of healthcare logistics, our research was inspired by the complexity of mixed constraints to deeply understand the complexities of UMOTP. The summary of our contribution lies in the introduction of a weighting method, which provides DMs with a great tool to organize optimal solutions. A major application lies in optimizing medical supply chains, where uncertainties in demand for critical items such as medicines and devices are prevalent. By assigning weights judiciously, our approach goes beyond traditional limitations, empowering DMs to deal with uncertainties with a high sense of accuracy. Moreover our methodology ensures that transportation routes are not only efficient but also in line with the timely delivery requirements of healthcare providers, facilitating a feat and responsive medical supply chain.

This innovation is especially important in health care, where the delicate balance between efficiency, cost-effectiveness, and patient satisfaction shapes the landscape. As we conclude this exploration, our proposed weighted method emerges as radiance in healthcare logistics optimization. It not only tackles the implicit challenges of the transportation problem but also does so with a keen awareness of the unique demands of the healthcare environment. The weighted approach presented here invites healthcare DMs to embark on a journey of micro-optimization, leading to better patient care, streamlined logistics, and informed DMs. By visualizing the rankings, DMs gain information about which method gives best compromise solution close to the optimal solution. This method becomes a compass, guiding healthcare professionals toward options that excel in accuracy, efficiency, and optimal patient outcomes.

In healthcare logistics, our proposed weighting method for UMOFTP brings a transformative approach. Designed to optimize critical areas such as the medical supply chain, patient-centered transportation, drug distribution, and blood and vaccine transportation, it aligns decisions with healthcare priorities. By considering uncertainties and judiciously determining weights, this method ensures efficient and patient-centric transportation, thereby enhancing the overall healthcare experience. It emerges as a strategic compass that navigates DMs through the complexities of healthcare logistics, provides customized solutions, and prioritizes the critical objectives of the healthcare sector.

Acknowledgment statement

The authors would like to extend their sincere appreciation to Researchers Supporting Project number (RSP2024R472), King Saud University, Riyadh, Saudi Arabia.

References

[1] V. D. Joshi, J. Singh, R. Saini, and K. S. Nisar, "Solving multi-objective linear fractional transportation problem under neutrosophic environment," *J. Interdiscip. Math.*, vol. 22, no. 1, pp. 123–136 (2022).

[2] V. D. Joshi, S. S. Naharwar, J. Singh, and K. S. Nisar, "An improved solution approach for solving multi-objective linear and linear fractional transportation problem," *J. Interdiscip. Math.*, vol. 26, no. 1, pp. 133–143 (2023).

[3] M. A. Nomani, I. Ali, and A. Ahmed, "A new approach for solving multi-objective transportation problems," *Int. J. Manag. Sci. Eng. Manag.*, vol. 12, pp. 165–173 (2016).

[4] S. A. Jalil, S. Javaid, Z. Asim, "A model for uncertain multi-objective transportation problem with fraction objection," *Int. J. Oper. Res.,* vol. 14, no. 1, pp. 11–25 (2017).

[5] S. Majumder, S. Kar, and T. Pal, "Uncertain multi-objective Chinese postman problem," *Soft Comput.,* vol. 23, pp. 11557–11572 (2019).

[6] S. Uddin, M. Miah, A. A. Khan, and A. Arjani, "Goal programming tactic for uncertain multi-objective transportation problem using fuzzy linear membership function," *Alex. Eng. J.,* vol. 60, no. 2, pp. 2525–2533 (2021).

[7] V. D. Joshi, S. S. Naharwar, J. Singh, and K. S. Nisar, "A new solution procedure for multi-objective linear fractional transportation problem with rough parameters," *J. Interdiscip. Math.,* vol. 26, no. 1, pp. 121–132 (2023).

[8] V. D. Joshi, K. Agarwal, and J. Singh, "Goal programming approach to solve linear transportation problem with multiple objectives," *J. Comput. Anal. Appl.*, vol. 31, no. 1, pp. 127–139 (2023).

[9] V. D. Joshi, P. Agarwal, and A. Kumar, "Fuzzy transportation planning: a goal programming tactic for navigating uncertainty and multi-objective decision making," *Int. J. Interact. Des. Manuf.* (2023).

[10] R. N. Mondal, M. R. Hossain, and S. Uddin, "Solving transportation problem with mixed constraints," in Proc. 2012 Int. Conf. Ind. Eng. Oper. Manag., Istanbul, Turkey, vol. 3, no. 6, Jul. (2012).

[11] S. Gupta, I. Ali, and A. Ahmed, "Multi-objective capacitated transportation problem with mixed constraint: a case study of certain and uncertain environment," *Opsearch*, vol. 55, pp. 447–477 (2018).

[12] S. Agarwal and S. Sharma, "A shootout method for time minimizing transportation problem with mixed constraints," *Am. J. Math. Manag. Sci.,* vol. 39, no. 4, pp. 299–314 (2020).

[13] B. Liu, Uncertain Theory, 2nd ed., Berlin: Springer-Verlag (2007).

[14] B. Liu, "Fuzzy Process Hybrid Process and Uncertain Process," *J. Uncertain Syst.,* vol. 2, no. 1, pp. 3–16 (2008).

[15] B. Liu, Theory and Practice of Uncertain Programming, 2nd ed., Berlin: Springer-Verlag (2009).

[16] S. Chakraborty, "TOPSIS and Modified TOPSIS: A comparative analysis," *Decis. Analytics J.,* vol. 2, pp. 2772-6622 (2022).

Received February, 2024