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Multi-Criteria Decision-Making Algorithm based on HyperSoft Set for Civil Litigation Efficiency Evaluation in the Context of Artificial Intelligence

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Abstract: Artificial Intelligence (AI) is increasingly being integrated into civil litigation to enhance efficiency, reduce costs, and improve decision-making accuracy. This study evaluates the effectiveness of AI-driven tools in civil litigation efficiency using a multi-criteria decision-making (MCDM) framework. Key evaluation criteria include case processing speed, judicial decision accuracy, cost reduction, transparency, accessibility, and AI adoption rates. Two MCDM methods are used in this study such as LMAW to compute the criteria weights and the CoCoSo method to rank the alternatives. We use the concept of the HyperSoft set to deal with various criteria and sub criteria in the evaluation problem. We conducted a case study with eight criteria and ten alternatives to show the validation of the proposed approach. The sensitivity analysis is conducted to show the stability of the proposed approach.

Keywords: HyperSoft Set; CoCoSo Method; Artificial Intelligence; Civil Litigation.

1. Introduction

The rapid advancements in Artificial Intelligence (AI) have significantly transformed various industries, including the legal sector. In the realm of civil litigation, AI-powered tools are being integrated to improve efficiency, streamline legal processes, and reduce the burden on courts. Traditional litigation is often characterized by lengthy case proceedings, high costs, and complex legal research, all of which can hinder access to justice. With AI-driven innovations such as predictive analytics, natural language processing (NLP), and automated document review systems, the landscape of civil litigation is evolving toward greater efficiency and transparency[1], [2]. Evaluating the effectiveness of AI in civil litigation efficiency is crucial to understanding its potential, limitations, and impact on legal systems. One of the key benefits of AI in civil litigation is its ability to accelerate case processing times. AI-driven case management systems and automated legal research tools can reduce the time required for attorneys and judges to analyze documents, identify relevant precedents, and make informed decisions[3], [4].

Moreover, AI-powered predictive analytics can assess case outcomes based on historical data, enabling litigants to make better strategic decisions before proceeding to court. However, while these advancements contribute to efficiency, concerns about accuracy, bias, and ethical considerations remain significant challenges that require continuous evaluation and refinement.

Cost reduction is another major advantage associated with AI-driven litigation systems. Automated document review, AI-assisted contract analysis, and virtual legal assistants can help reduce the workload of legal professionals, thereby lowering litigation costs for both clients and the judiciary. Small and medium-sized law firms, which often struggle with resource constraints, can particularly benefit from these technologies. However, the adoption of AI tools varies across legal jurisdictions, with some courts embracing AI-driven solutions while others remain skeptical about their reliability and fairness[5], [6]. This disparity in implementation necessitates a comprehensive evaluation of AI's impact on litigation efficiency across different legal systems.

The integration of AI in civil litigation also raises important questions regarding transparency and fairness. While AI systems can analyze large volumes of legal data and identifying patterns, they may inadvertently reinforce existing biases if trained on flawed datasets. Ensuring that AI-driven legal tools align with judicial ethics, procedural fairness, and data privacy regulations is essential for maintaining public trust in the legal system. Moreover, the need for human oversight in AI-assisted legal decision-making remains crucial to mitigate risks associated with algorithmic errors and bias.

Given these evolving dynamics, conducting a systematic evaluation of AI's role in civil litigation efficiency is imperative. This study employs a multi-criteria decision-making (MCDM) framework to assess AI-driven litigation tools based on factors such as processing speed, cost-effectiveness, accuracy, transparency, accessibility, and user adoption[7], [8]. By examining these criteria, this research aims to provide insights into how AI can be optimally integrated into legal proceedings, ensuring a balanced approach that enhances efficiency while upholding justice and fairness.

Several groups of academics from a variety of fields, including supply chain and manufacturing, business and management, energy, and construction, have expanded their study on MCDM. To handle a decision-making problem, MCDM offers a variety of techniques with various algorithms and structures. This type of decision-making issue involves several variables (criteria) and alternatives (choices, solutions). The function of each MCDM approach is to generate the weights of the criteria and the alternatives (score or ranking). Depending on their needs and the intricacy of the challenge, experts and researchers from various fields would use such techniques. This area of business analytics has made significant contributions to the solution of issues including ranking, sorting, classification, and assessment.

To identify the best answer to multi-criteria decision-making problems, a variety of decision-making techniques have been created during the past three decades. The MCDM literature demonstrates the rapidly expanding use of CoCoSo. Experts from a variety of fields attempt to use CoCoSo because of its simple algorithm and ease of use[9], [10].

The main contributions of this study are organized as follows:

We propose an MCDM method to compute the criteria weights and ranking the alternatives.

We use The LMAW method to compute the criteria weights and the CoCoSo method to rank the alternatives.

We use the HyperSoft Set to deal with various values of alternatives.

Sensitivity analysis is conducted to show the stability of ranks of the alternatives under different cases and criteria.

2. LMAW-CoCoSo Model

This section shows the steps of the LMAW with the CoCoSo methodology. We used the LMAW methodology to compute the criteria weights and the CoCoSo methodology to rank the alternatives.

Steps of the LMAW methodology are organized as follows[11], [12]:

Prioritize the criteria based on the opinions of experts and decision makers.

Define the absolute anti-ideal point x_{AIP}

$$x_{AIP} = \frac{x_{min}}{S} \tag{1}$$

S is a number greater than the base of logarithm (A).

Determine the relation between the elements of priority vector and x_{AIP}.

$$r = \frac{x_{cn}}{x_{AIP}} \tag{2}$$

Where x_{cn} refers to the value from the relation vector.

Compute the criteria weights.

$$w_j = \frac{\log_A r}{\log_A b} \tag{3}$$

$$b = \prod_{j=1}^{n} r \tag{4}$$

Steps of the CoCoSo method.

By merging concepts from compromised solutions, such as power weight aggregation and mean evaluation weighting, CoCoSo begins to identify the best option. Here is an interpretation of the CoCoSo step-by-step solution:

This method's first step is to formulate the decision issue, which includes identifying the criteria, alternatives, weights for each criterion, and the direction of optimization. After that, we ought to create a preliminary choice matrix. Accessing a data collection or decision-making preference (using linguistic values) should be used to carry out this activity[13], [14].

Normalizing the matrix is the second phase, which is accomplished using two methodologies for the benefit and non-benefit categories of criteria, such as product pricing or energy use, among others.

CoCoSo calculates two methods to aggregate the weights of the criteria in the decision-making process. The first is to add up the normalized matrix's multiplication by the weight values (S), and the second is to add up the normalized matrix's power weight (P).

We must combine the S and P variables in this phase. We compute a total of relative WSM and WPM scores in relation to the best, then we compute the arithmetic mean of the sums of WSM and WPM scores. The balanced compromise of the WSM and WPM model scores is released.

The U values are used to establish the alternatives' final ranking.

To help decision experts confirm the results, CoCoSo's applicability is compared to other comparable tools or sensitivity analysis tests. The CoCoSo implementation's mathematical formulation is shown here.

Determine the decision matrix

$$x_{ij} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}; i = 1, \ldots, m; j = 1, \ldots, n \quad (5)$$

Normalize the decision matrix

The decision matrix is normalized for beneficial and non-beneficial criteria such as:

$$q_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad (6)$$

$$q_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad (7)$$

Compute the power weight of decision matrix and total weighted decision matrix

$$S_i = \sum_{j=1}^{n} w_j q_{ij} \quad (8)$$

$$P_i = \sum_{j=1}^{n} (q_{ij})^{w_j} \quad (9)$$

Compute the relative weights of the alternatives based on a set of strategies.

$$U_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)} \quad (10)$$

$$U_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i} \quad (11)$$

$$U_{ic} = \frac{\varphi(S_i)+(1-\varphi)(P_i)}{\left(\varphi \max_i S_i+(1-\varphi) \max_i P_i\right)} \; 0 \leq \varphi \leq 1 \quad (12)$$

Rank the alternatives based on

$$U_i = (U_{ia}U_{ib}U_{ic})^{\frac{1}{3}} + \frac{1}{3}(U_{ia}+U_{ib}+U_{ic}) \quad (13)$$

HyperSoft Set

Smarandache extends the soft set by introducing the HyperSoft Set to deal with various criteria and sub criteria. HyperSoft set can transform the single-criterion function into a multi-criteria function[15], [16].

Let U and L be a universe of discourse and non-empty set in U. The powerset of U is a P(L).

Let $d_1, d_2, \dots, d_n$ $where\ n \geq 1$ be a distinct criteria and their values can be represented as $D_1, \dots D_n$ $with\ D_i \cap D_j = \emptyset\ for\ i \neq j\ and\ i, j \in 1,2, \dots, n$

The pair $(F, D_1 \times D_2 \times D_3 \times \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \times D_n)$ where $D_1 \times D_2 \times D_3 \times \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \times D_n$ presents the cartesian product with $F{:}\, D_1 \times D_2 \times D_3 \times \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \times D_n \to P(L)$ is called a HyperSoft Set.

3. Results and Discussion

We present an application to show the criteria weights and ranking the alternatives. The CoCoSo method is used to rank alternatives. Several variants of the CoCoSo approach have been adopted and used in several case studies since its inception. From the original or classical CoCoSo to interval or gray models and a few fuzzy expansions. Researchers exploited CoCoSo intuitive and relaxed algorithm to concentrate on its usefulness in ambiguous situations. To the best of our knowledge, after reviewing every resource that applied CoCoSo, none of them attempted to utilize an enhanced or modified version of the program. We saw several mistakes when using the CoCoSo technique on exceptional occasions, even though this is a thorough complete ranking approach, and the structure has been tested extensively. This scenario will be presented and discussed below.

We employed several techniques, including CoCoSo, in our study on the application of MCDM techniques for Civil Litigation Efficiency Evaluation in the Context of Artificial Intelligence. There are eight criteria that allow you to choose them based on the accommodation that is available. The criteria of this study are organized as follows:

User Satisfaction and Adoption Rate (High, Moderate, Low), Accessibility to Justice (Broad, Standard, Limited), AI-Assisted Legal Research Efficiency (Efficient, Standard, Inefficient), Cost Reduction in Litigation (Significant, Moderate, Minimal), Judicial Decision Accuracy (High, Moderate, Low), Data Security and Privacy Protection (Strong, Moderate, Weak), Case Processing Speed (Fast, Moderate, Slow), Transparency and Fairness (High, Moderate, Low). The alternatives of this study are:

Online Dispute Resolution System, AI-Enabled Court Transcription System, Predictive Analytics for Case Outcomes, AI-Powered Sentencing and Judicial Decision Support, AI-Assisted Legal Research Platform, AI-Based Legal Chatbots, Blockchain-Based Legal Data Security System, Automated Document Review System, Natural Language Processing (NLP) for Legal Texts, AI-Powered Case Management System

The results of the LMAW methodology are presented as:

We prioritize the criteria by the opinions of the experts.

We define the absolute anti-ideal point x_{AIP} using Eq. (1).

Eq. (2) is used to determine the relation between the elements of priority vector and x_{AIP}.

Eq. (3) is used to compute the criteria weights as shown in Fig 1.

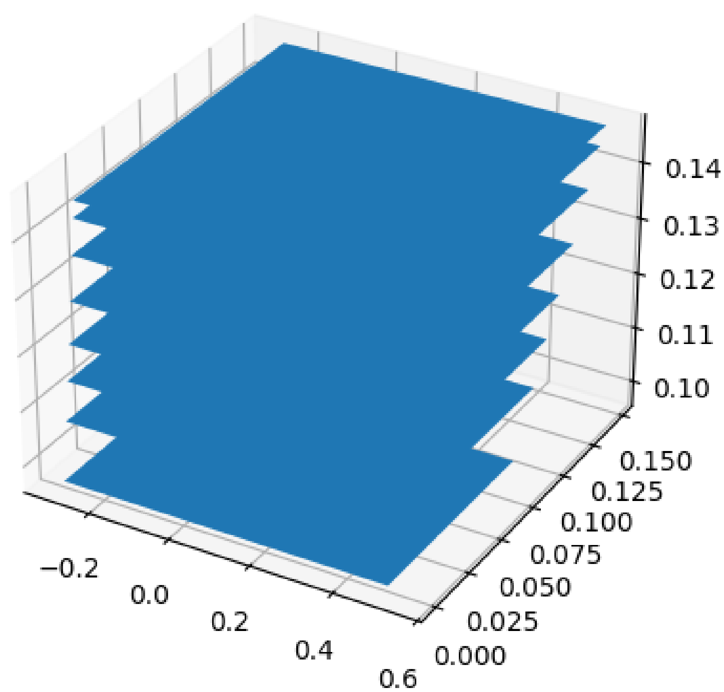

Fig 1. The criteria weights.

We are ranking the alternatives we use the concept of the HyperSoft set to deal with various criteria and values. This study selects the best values such as:

{High}, {Broad}, {Efficient}, {Moderate}, {High}, {Strong}, {Fast}, {Moderate}

Results of the CoCoSo method.

We determine the decision matrix using Eq. (5). We use scale between 0.1 to 0.99 to evaluate the criteria and alternatives based on three experts and decision makers. Then we combine the decision matrix into a single matrix as shown in Fig 2.

We normalize the decision matrix using Eq. (6) as shown in Fig 3.

Then we compute the power weight of the decision matrix and total weighted decision matrix using Eq. (8) and Eq. (9) as shown in Fig 4 and Fig 5.

Then we compute the relative weights of the alternatives based on a set of strategies using Eqs. (10-12).

Then we rank the alternatives based on U_i using Eq. (13). Fig 6 shows the rank of the alternatives.

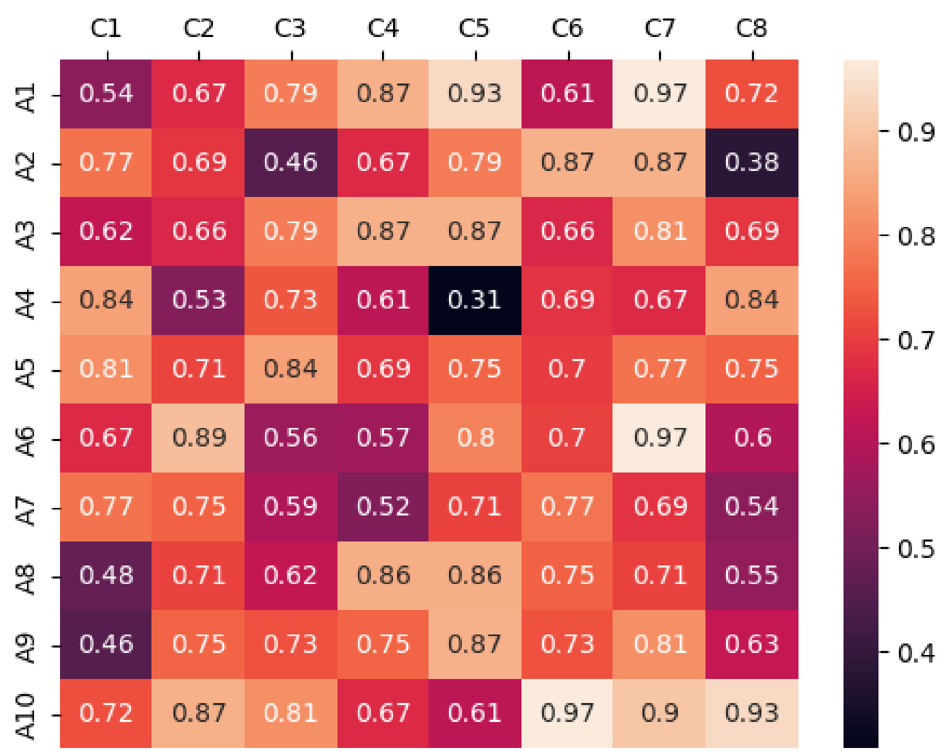

Fig 2. The combined decision matrix.

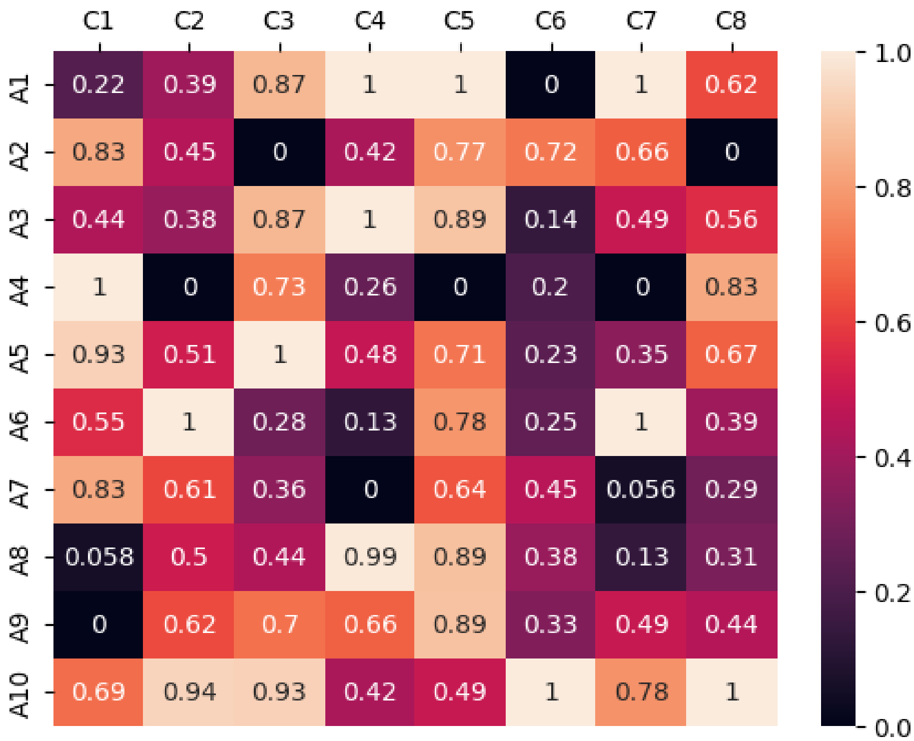

Fig 3. The normalized decision matrix.

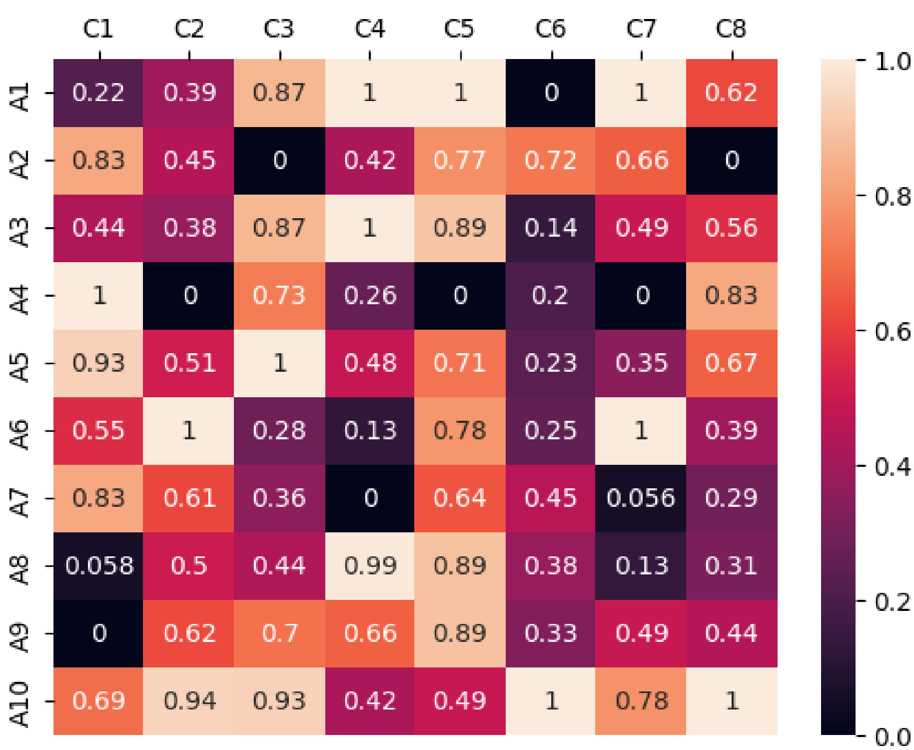

Fig 4. The weighted decision matrix.

Fig 5. The power weight decision matrix.

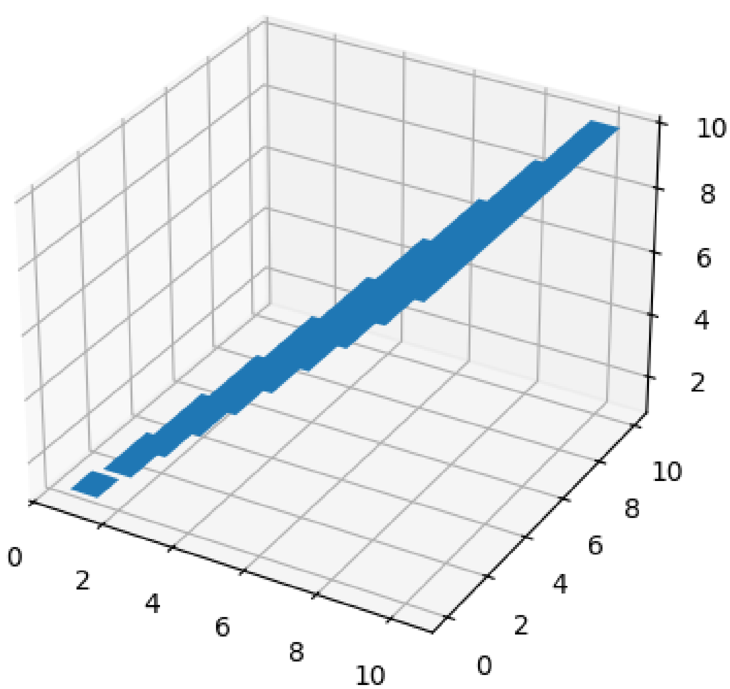

Fig 6. The rank of alternatives.

4. Analysis

Sensitivity analysis is a powerful methodological tool used to assess how variations in input parameters influence the outcomes of a given model or decision-making process. It is widely applied across disciplines, including engineering, economics, environmental sciences, and MCDM. By systematically adjusting key factors within a model, sensitivity analysis helps to identify which variables have the most significant impact on results, ensuring robust decision-making even in uncertain conditions. This approach is particularly valuable when dealing with complex systems where small changes in input can lead to substantial shifts in outputs, highlighting the stability and reliability of analytical frameworks.

This study conducted the sensitivity analysis to show the validation of the proposed approach and stability of the ranks. We change the values of φ between 0 and 1 to show different ranks of the proposed approach. Fig 7 shows the different values of U_i. Then we rank the alternatives based on these cases. Fig 8 shows the different ranks of the proposed approach. We show alternative 10 is the best and alternative 4 is the worst. We show the ranks are stable under different cases.

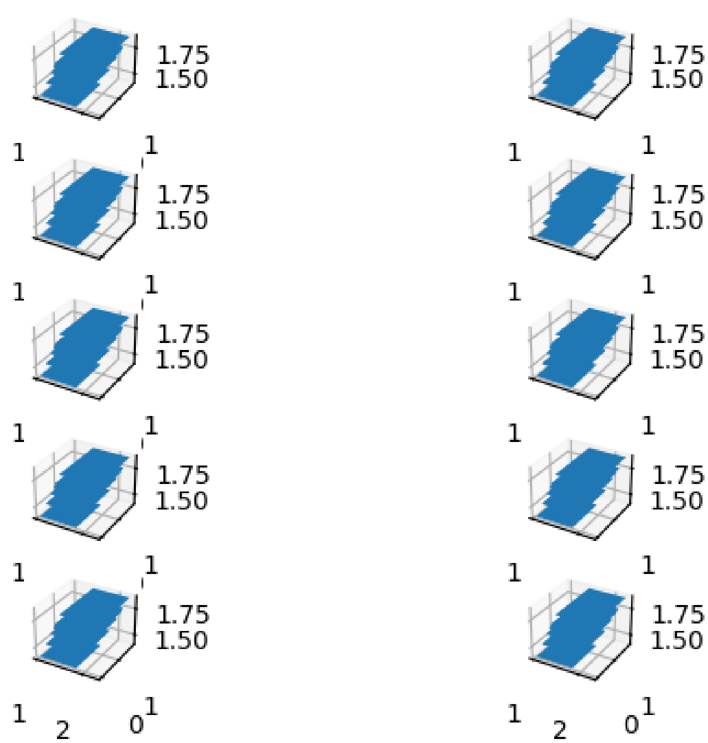

Fig 7. Different values of U_i.

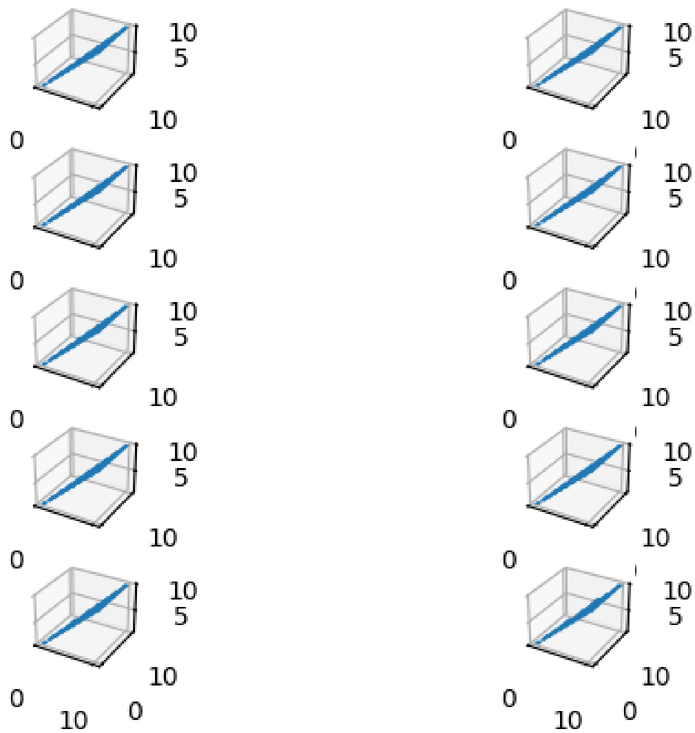

Fig 8. Different ranks of alternatives.

In the context of decision-making, sensitivity analysis enhances transparency and confidence in model-driven conclusions. It enables researchers and policymakers to prioritize influential criteria, optimize resource allocation, and mitigate risks associated with uncertainties in data. Sensitivity analysis provides different perspectives on how model parameters interact. By incorporating sensitivity analysis into evaluation processes, organizations can make more data-driven, resilient, and adaptable decisions, ensuring that strategies remain effective under varying real-world conditions.

5. Conclusions

The adoption of AI in civil litigation has the potential to revolutionize legal proceedings by reducing case processing times, lowering litigation costs, and improving judicial decision-making accuracy. The study's findings suggest that AI-powered tools such as automated legal research, predictive analytics, and document review systems contribute significantly to enhancing litigation efficiency. However, while AI enhances speed and accessibility, concerns regarding data security, algorithmic bias, and ethical transparency must be addressed to maintain trust in the legal system. A balanced approach combining AI-driven automation with human oversight is crucial to ensuring both efficiency and fairness in civil litigation.

This study proposed an MCDM method to compute the criteria weights by the LMAW method and ranking the alternative by the CoCoSo method. We used the HyperSoft set to deal with criteria and sub criteria. Eight criteria and ten alternatives are used in this study. The results show alternative 10 is the best and alternative 4 is the worst. We conducted sensitivity analysis to show the stability of the ranks. The results show the results of the proposed approach are stable in different cases.

Despite the advantages AI brings to civil litigation, the unequal adoption of AI technologies across legal jurisdictions remains a major challenge. Some legal systems have embraced AI-driven case management, while others remain cautious due to concerns about reliability, bias, and regulatory uncertainties. A structured approach to AI implementation, supported by regulatory frameworks, ethical guidelines, and continuous monitoring mechanisms, is necessary to standardize AI's role in litigation.

Another critical finding of this research is the need for data integrity and security measures in AI-driven legal systems. Given the sensitive nature of legal data, AI-powered litigation tools must comply with data privacy regulations, encryption standards, and cybersecurity best practices to ensure confidentiality and prevent misuse. Additionally, efforts to enhance AI transparency and explainability can help build confidence in AI-assisted judicial decision-making.

AI presents a transformative opportunity for improving civil litigation efficiency, but its implementation must be carefully managed to ensure fairness, accuracy, and ethical compliance. The integration of AI in the legal domain should be guided by strategic policy frameworks, interdisciplinary collaboration, and ongoing assessments to mitigate risks while maximizing benefits. By leveraging AI responsibly, the legal sector can achieve a more efficient, accessible, and transparent judicial system, ultimately enhancing the delivery of justice in an increasingly digital world.

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