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# A machine learning-enhanced fuzzy decision-making model for blockchain platform selection in healthcare systems

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ABSTRACT

The healthcare sector is experiencing unprecedented growth in the volume and complexity of its data, driven by the increasing digitization of patient records, the interconnectedness of devices, and the involvement of diverse stakeholders. While blockchain technology offers significant potential to address critical issues of security, transparency, integrity, and accessibility, selecting an appropriate blockchain model for healthcare remains challenging due to the multiplicity of technical, operational, and regulatory considerations. This study proposes a novel methodological framework that systematically integrates Machine Learning (ML) and Multi-Criteria Decision-Making (MCDM) methods to enhance the stability and reliability of the decision process. First, Agglomerative Hierarchical Clustering (AHC) is applied to eliminate redundancy and reduce dimensionality among the large set of decision criteria identified from the literature. Next, Proportional Picture Fuzzy Sets (PPFSs) are employed to more accurately capture the complexities of human judgment, including hesitation, disagreement, and partial agreement, providing a more detailed picture than traditional fuzzy methods. The relative importance of the criteria is determined using the PPFS-based Weights by ENvelope and SLOpe (WENSLO) approach, which ensures data-driven and objective weight assignment under uncertainty. Subsequently, blockchain alternatives are ranked through the PPFS-based Complex Proportional Assessment (COPRAS) method, which proportionally incorporates both favorable and unfavorable attributes. The findings indicate that private (permissioned) blockchain architectures emerge as the most suitable option for healthcare settings, largely because they perform better on critical criteria such as data decentralization, efficiency, and accessibility. Finally, a sensitivity analysis and comparative assessment are performed to check the robustness and stability of the developed model.

## 1. Introduction

The rapid expansion of data in the healthcare sector, coupled with the rise of multi-stakeholder models and the increasing volume of health records containing highly sensitive and confidential information, has spotlighted the pressing need to address challenges related to security, transparency, integrity, and accessibility (Kruse et al., 2017). In this context, blockchain technology, with its decentralized architecture and immutable record-keeping capabilities, presents a promising solution for enhancing the management and protection of healthcare data (Murugeswari and Ganesan, 2024). Blockchain provides robust security and traceability across a wide range of applications, including ensuring the accuracy of patient records, preventing drug counterfeiting, monitoring supply chains, and enabling transparent claims management (Tseng et al., 2018; Yue et al., 2016). The vulnerabilities exposed in healthcare supply chains, particularly in the post-COVID-19 context, have highlighted the critical need to adopt blockchain-based systems to improve transparency, resilience, and operational efficiency. Effectively managing health data in a secure, traceable, and shareable manner not only enhances patient safety but also supports research initiatives, public health strategies, and evidence-based policy-making (van Gaans et al., 2015). However, some structural and administrative prerequisites exist for incorporating blockchain technology in healthcare systems.

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**Nomenclature**

| | |
|---|---|
| AHC | Agglomerative Hierarchical Clustering |
| AHP | Analytic Hierarchy Process |
| AIS | Anti-Ideal Solution |
| ALWAS | Adaptive Linear Weighted Averaging System |
| AI | Artificial Intelligence |
| ANP | Analytic Network Process |
| CODAS | COmbinative Distance-based ASsessment |
| COPRAS | COmplex PRoportional ASsessment |
| CRADIS | Compromise Ranking of Alternatives from Distance to Ideal Solution |
| CRITIC | CRiteria Importance Through Intercriteria Correlation |
| DM | Decision-Maker |
| DL | Deep Learning |
| EHR | Electronic Health Records |
| EWM | Entropy Weight Method |
| F-FUCOM | Fuzzy Full Consistency Method |
| FQFD | Fuzzy Quality Function Deployment |
| GRA | Grey Relational Analysis |
| IoMT | Internet of Medical Things |
| IoT | Internet of Things |
| IS | Ideal Solution |
| KNN | K-Nearest Neighbors |
| ML | Machine Learning |
| MARCOS | Measurement Alternatives and Ranking according to COmpromise Solution |
| MCDM | Multi-Criteria Decision-Making |
| NIS | Negative-Ideal Solution |
| PIS | Positive-Ideal Solution |
| PPF-CODAS | Proportional Picture Fuzzy CODAS |
| PPF-COPRAS | Proportional Picture Fuzzy COPRAS |
| PPF-TOPSIS | Proportional Picture Fuzzy TOPSIS |
| PPF-WENSLO | Proportional Picture Fuzzy WENSLO |
| PPFN | Proportional Picture Fuzzy Number |
| PPFS | Proportional Picture Fuzzy Set |
| SF-WZICS | Spherical Fuzzy Weighted with Zero Inconsistency |
| SVM | Support Vector Machine |
| TOPSIS | Technique for Order Preference by Similarity to Ideal Solution |
| WENSLO | Weights by ENvelope and SLOpe |
| WoS | Web of Science |

Blockchain-based solutions can be effectively employed only by creating intra-system cooperation mechanisms, updating legal legislation, and implementing unified standards, besides infrastructural investments (Saeed et al., 2022). Additionally, the transparency, accountability, and cybersecurity features offered via blockchain can assist in creating more resilient trust relationships between healthcare sector stakeholders (A. A. Khan et al., 2023). However, incompatibility of current data formats in systems, absence of regulatory guidelines, and technology adaptation issues are some of the important hurdles to be overcome. In the near future, blockchain technology will embed other digital transformation drivers such as Artificial Intelligence (AI), big data, and Internet of Things (IoT) to become the pillars of smarter and better-integrated healthcare systems (Fatoum et al., 2021).

One of the greatest challenges in integrating blockchain technology into health systems is determining which blockchain model and platform to implement. Different blockchain solutions differ from each other based on different technical as well as operational factors like scalability, transaction rate, security, data privacy, and flexibility (Wu and Wang, 2024). For instance, public blockchains provide full transparency and immutability, whereas private blockchains are designed to ensure data privacy and controlled access. Hybrid models, which combine features of both public and private blockchains, are considered in the literature to offer a more balanced and effective solution for healthcare applications (Mishra et al., 2023). Beyond technical considerations, technology selection in the healthcare sector should involve a comprehensive evaluation of multiple criteria, including legal and regulatory requirements, data protection frameworks, cost-effectiveness, and the ease of integration with existing systems (Dehshiri and Amiri, 2024).

In this multi-criteria technology selection context, it is crucial to adopt systematic decision support approaches rather than relying on traditional, intuitive judgments. When choosing among blockchain platforms, it is necessary to evaluate not only technical performance but also a range of other factors, including security, data privacy, scalability, transaction costs, regulatory compliance, and user acceptability. Accordingly, Multi-Criteria Decision-Making (MCDM) methods offer an effective and structured framework for guiding the technology selection process (Bonab et al., 2023; Radovanović et al., 2023; Stević et al., 2024). However, particularly in the healthcare sector, the complex data structures, uncertainties, and variability inherent in decision-making processes cannot be adequately addressed through fixed-weight evaluation approaches (Rajkomar et al., 2019; Reddy et al., 2019). In this context, integrating Machine Learning (ML) techniques into MCDM frameworks has emerged as a critical requirement. Since ML algorithms analyze historical decision data in conjunction with user preferences and feedback from system responses, they enable the determination of criteria weights in an objective, adaptive, and dynamic manner (Wang et al., 2013). Particularly in modern healthcare systems that involve large-scale data sources, AI and ML models can capture complex relationships among criteria while reducing subjectivity and bias in decision-making processes (Wang and Tang, 2025). Moreover, given the constantly evolving legal frameworks and technological developments in the healthcare sector, ML-based MCDM systems offer adaptable and updatable mechanisms, enabling more resilient and sustainable decision support solutions over the long term (Panch et al., 2019; Selvaraj and Sundaravaradhan, 2020; Shickel et al., 2017). Therefore, the integration of MCDM and ML represents a pivotal approach for improving decision accuracy and enhancing the effectiveness of practical applications.

In this study, the methodological framework is structured in a systematic and sequential manner. First, the criteria for evaluating blockchain technologies in the healthcare domain are identified through an extensive review of the literature. Given that many criteria exhibit overlap or similarity, their dimensionality is reduced using the Agglomerative Hierarchical Clustering (AHC) method, serving as an ML-based pre-processing step. Subsequently, MCDM techniques are incorporated into the analysis. Within this framework, the Proportional Picture Fuzzy Weights by ENvelope and SLOpe (PPF-WENSLO) method is employed to determine the relative weights of the decision criteria, while the Proportional Picture Fuzzy COmplex PRoportional Assessment (PPF-COPRAS) method is used to rank the alternatives. A distinctive feature of this study is that both stages are conducted within the Proportional Picture Fuzzy Set (PPFS) environment. The use of PPFSs allows for a more accurate representation of the uncertainty, vagueness, and hesitation inherent in expert judgments compared to conventional fuzzy models. Integrating PPFS with WENSLO and COPRAS enhances decision-making in several ways: WENSLO under PPFS enables the assignment of criteria weights that proportionally reflect Decision-Makers' (DMs) uncertainty and partial agreement, while COPRAS within the PPFS framework ensures that alternative rankings account not only for crisp evaluations but also for the proportional intensity of hesitation and indeterminacy. Consequently, the combined approach yields more robust, consistent, and reliable decision outcomes in contexts characterized by complex trade-offs and incomplete information.

This methodological synergy demonstrates how the integration of PPFSs, WENSLO, and COPRAS (i.e., PPF-WENSLO-COPRAS) establishes a robust paradigm for MCDM applications, particularly in contexts where uncertainty and subjectivity are unavoidable. The PPFSs framework is more sophisticated than traditional fuzzy sets, as it enables experts to express proportional relationships among membership, indecision, and opposition degrees, rather than requiring precise numerical specification of membership values (Kahraman, 2024). This approach enables experts to articulate their judgments in a more natural, straightforward, and balanced manner. In contrast, the PPF-WENSLO method provides a fully data-driven and objective process for assigning criteria weights, eliminating reliance on subjective expert input. It provides optimal weights for both cost-type and benefit-type criteria by examining the behavior of the criterion in terms of slope and envelope. COPRAS is an open and easy-to-calculate ranking method that evaluates options proportionally, considering both favorable and unfavorable attributes (Ahemad et al., 2023). The integration of these three methods provides a more intuitive, objective, and unbiased decision support mechanism for experts within the weighting process, and an efficient and transparent ranking system.

In the context of assessing blockchain technology applications in healthcare, a wide array of factors is considered. Nevertheless, the multiplicity and overlap among these factors often hinder systematic decision-making and lead to irregular evaluation outcomes. Applications in the literature that aim at systematically minimizing such factors through ML approaches are only rarely met. Therefore, in this study, the AHC method was used to analyze and reduce the criteria obtained from the literature. The primary reason for choosing this method is that it allows for hierarchical grouping of data and interpretation using a dendrogram when the number of clusters is not known in advance. Furthermore, this method works with flexible similarity criteria on small and medium-sized datasets, allowing for the analysis of complex decision structures in a clear and visualizable manner. In addition, since weight procedures often rely on the expertise of specialists, they remain susceptible to subjectivity; the use of data-driven, unbiased, and non-parametric methods is severely limited. Traditional fuzzy sets are primarily used for modeling uncertainty, while more advanced structures that allow DMs to express membership, opposition, and indecision rates more freely, such as PPFSs, have not been implemented commonly enough. But the number of models where the criteria for weighting and alternative ranking phases are handled with a holistic method integration in one common logical roof is also very few.

This work offers a logical and systematic model of decision support for identifying blockchain technologies in the health sector. It interprets and transforms equivalent and numerous criteria into a more meaningful framework. It also makes a novel methodological contribution to the literature by merging the PPF-WENSLO and PPF-COPRAS approaches for the first time. The aim of the study is for both researchers and practitioners. For researchers, it presents a novel integrated approach based on AHC, PPFSs, WENSLO, and COPRAS and opens a new door in the integration of ML and MCDM methods. For practitioners, it analyzes both blockchain platforms used in the healthcare field and aims to help based on selection criteria.

In this context, the following research questions will be addressed by this study:

1. How can AHC be integrated into MCDM frameworks to improve alternative prioritization?
2. Which blockchain technologies are widely adopted in healthcare, and what criteria guide their selection?
3. What outcomes emerge from applying PPF-WENSLO-COPRAS with selecting healthcare blockchain technologies?
4. How does this integrated approach compare with alternative methods in terms of effectiveness?

The rest of the manuscript is structured as follows. The relevant literature is reviewed in Section 2, and the case study and hierarchical structure are the main topics of Section 3. Methodologies and the research framework are covered in Section 4. The outcomes of the application, conclusions, and sensitivity analysis are given in Section 5. In addition, Section 6 ends with suggestions for additional research.

## 2. Literature review

To provide a clearer understanding of the studies utilized in this study, the literature was reviewed in two parts. The first part covers ML-based studies, and the second part covers MCDM-based studies in the healthcare sector.

### *2.1. Blockchain and ML-based healthcare*

Blockchain technology is gaining increasing attention in healthcare due to its architecture that supports secure, immutable, and transparent data storage. It has the potential to be implemented in various areas such as secure sharing of Electronic Health Records (EHR), patient privacy, transparent supply chain management, and traceability of insurance transactions. Increasing demands for digitalization, especially with the COVID-19 pandemic, have made it necessary to handle health data using decentralized networks securely. In this context, blockchain provides solutions for secure access to patient information, reliable identity verification, and the protection of transaction integrity.

Blockchain adoption in healthcare systems is not limited to data storage only; it also takes part in other functional areas such as drug supply chain, patient-centered care models, insurance claims, and telehealth services. However, the adoption of this technology requires consideration of multiple factors, including technical suitability, operational feasibility, security requirements, and regulatory compliance. Kaur et al., (2018) showed that while big data and ML are widely applied in healthcare, many existing systems fail to give sufficient attention to privacy and security. To overcome this limitation, they proposed a smart, secure healthcare information system that integrates ML with advanced protection mechanisms. Boddu et al., (2022) discussed that ML tools are increasingly used to enhance decision-making, detect critical diseases, and reduce medical errors in the pharmaceutical industry. An et al., (2023) applied ML techniques to medical data to improve diagnostic accuracy and identify meaningful patterns.

Studies also highlight that automation, big data, and cloud technologies improve safety, efficiency, and production accuracy. There are also some more research works which have demonstrated the use of ML algorithms to enhance the efficiency and accuracy of time-series healthcare metrics. Kumari et al., (2023) examined how ML and Deep Learning (DL) are increasingly applied in healthcare, especially for tasks such as predictive analytics, medical imaging, and personalized treatment. They utilized bibliometric analysis using WoS data and tools like R-bibliometrix and VOSviewer to map research trends, collaborations, and influential contributions in this field. They indicated that ML and DL have become essential approaches for handling large and complex healthcare data. Saraswat et al., (2023) investigated how ML techniques, applied by various researchers through methods such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), neural networks, and decision trees, help uncover hidden patterns in large healthcare datasets. They found that these approaches significantly improve disease detection and diagnostic accuracy. Sarker (2024) discussed a shift toward more personalized and effective care, as demonstrated by the predictive modeling approaches applied by the researchers. The author tested several ML algorithms on large patient datasets, with logistic regression emerging as the most accurate model.

### *2.2. Fuzzy decision-making model*

In this section, studies on fuzzy MCDM-based decision support systems are examined in detail. The decision support system suggested by

Mishra et al. (2023) employed interval-valued Pythagorean fuzzy systems to evaluate blockchain platforms within healthcare supply chains. It identified the most suitable blockchain infrastructure to ensure the validity and security of patient data. Criteria weighted using the PIPRECIA model and entropy measures were ranked through the MAIRCA model, enabling a multi-dimensional decision support process. Zarour et al. (2020) compared and analyzed the impact of various blockchain models on EHRs, focusing on their reliability and security. Using fuzzy Analytic Network Process (ANP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods, they identified which blockchain models should be prioritized by healthcare organizations. The results pointed out blockchain models that minimize security risks, ensure transaction traceability, and safeguard patient privacy. Gardas et al. (2022) proposed a fuzzy logic-based method for precise node selection in blockchain-based edge-IoT systems and addressed the utility of such systems in healthcare for ensuring precise data flow, especially in remote patient monitoring systems. Qahtan et al. (2022) examined blockchain applications in IoT-based healthcare systems, evaluating security and privacy criteria using Spherical Fuzzy Weighted with Zero Inconsistency (SF-WZICS) and Grey Relational Analysis (GRA)-TOPSIS methods. System comparisons were conducted by weighting attributes such as access control, user authentication, anonymity, and data integrity. The findings showed that blockchain enhances both data security and overall system efficiency in health IoT applications. Erol et al. (2023) proposed a decision model combining rough Analytic Hierarchy Process (AHP) and compromise programming methods to select the most appropriate blockchain platform for the healthcare sector. They compared system criteria to address the specific needs of healthcare institutions and ensured the selection of the optimal platform. The platforms were evaluated across multiple parameters, including scalability, security, transaction speed, and user base. The model proposed by Liu et al. (2024) employed a hybrid distance-based approach combined with AHP and Entropy Weight Method (EWM) to select blockchain platforms based on heterogeneous criteria. A highly relevant framework was presented to select blockchain platforms that possess the potential to adapt to the changing dynamics of the health sector. Pathak et al. (2023) presented a general guideline on how MCDM methods used in healthcare systems can be integrated with blockchain. The guideline outlined why and how blockchain-based systems should be prioritized for security, cost efficiency, and operational feasibility.

To have a better overview of the previous efforts made in the literature, Table 1 compares the most relevant studies. This wide literature review demonstrates that blockchain technology is increasingly taking strategic and critical roles in the healthcare industry. Both the reduction of technological complexity and the facilitation of systematic and original analysis to DMs are achieved by MCDM-based strategies. Blockchain-based solutions are expected to play a larger role in the future of the healthcare sector.

### 2.3. Research gaps

When the literature is examined, it is evident that various similar factors influence the selection of blockchain technologies adopted in the healthcare sector; however, these factors have not yet been systematically categorized and synthesized into a more robust framework. Further, current research primarily conducts the task of weighing criteria based on expert views, thereby increasing the possibilities for subjectivity and incongruence (Kizielewicz et al., 2024). When dealing with uncertainty, researchers typically rely on classical or intuitionistic fuzzy sets, and the use of more advanced, ratio-based methods such as PPFSs remains uncommon. Apart from all these, MCDM-based decision support models considering the specific requirements of the health sector (privacy, security, transaction efficiency, etc.) are extremely rare (Qahtan et al., 2022). For bridging such gaps, this research attempts to provide weighting without subjectivity, uncertainty modeling with a better fuzzy system, and consistent method integration through

**Table 1**
Summary of the most relevant and recent studies.

| Reference | Method | Findings | Sectoral Implementation |
|---|---|---|---|
| Zarour et al. (2020) | Fuzzy ANP, Fuzzy TOPSIS | Blockchain models utilized in EHR systems were compared; security and reliability are the key considerations. | Electronic Healthcare Records |
| Mishra et al. (2023) | IVPF-Entropy, PIPRECIA, MAIRCA | Blockchain healthcare supply chains were compared on different criteria; the novel approach was stable and effective. | Healthcare Supply Chain |
| Liu et al. (2024) | AHP, EWM, Hybrid TOPSIS | A weighted mixed approach was proposed to compare blockchain platforms; it was tested using intensive examples like the healthcare sector. | General Healthcare |
| Erol et al. (2023) | RAHP-E, RCP | A framework of multi-criteria decision support was proposed to select the most suitable blockchain platform for healthcare organizations. | Healthcare |
| Qahtan et al. (2022) | S-FWZIC, GRA-TOPSIS, BES | An IoT healthcare system ranking framework based on security and privacy attributes was proposed. The key criterion was access control. | IoT Healthcare |
| Chakraborty et al. (2023) | AHP, TOPSIS, PROMETHEE | A systematic MCDM approach classification in the healthcare domain was performed on 140 articles. AHP is the most widely used method. | General Healthcare |
| Gardas et al. (2022) | Fuzzy TOPSIS | The approach proposed for proper node selection in IoT-edge settings: attributes are energy, distance, and buffer space. | IoT/ Healthcare Related |
| Pathak et al. (2023) | Literature review | Theory explained MCDM approaches for healthcare blockchain implementation. | Healthcare |
| Khan & Ali, (2022) | F-FUCOM, FQFD | The implementation of pharma's circular supply chain management was inhibited or promoted by recognized inhibitors and facilitators. Blockchain technology emerged as the essential facilitator. | Medicine/ Healthcare |
| Krishankumar et al. (2024) | CRITIC, CRADIS-Copeland | Choice of a suitable blockchain service provider for data management by Internet of Medical Things (IoMT) in healthcare: privacy, communication capability, availability, and total cost are the choice criteria. | Healthcare/ IoMT |

(continued on next page)

**Table 1** (*continued*)

| Reference | Method | Findings | Sectoral Implementation |
|---|---|---|---|
| Demir (2025) | Grey DEMATEL | IoT technologies being selected in healthcare; security and data privacy are the most important considerations. | Healthcare |

simplifying the criteria with ML. In other words, we provides decision-making guidance to assist healthcare organizations in identifying the most appropriate blockchain solution.

Therefore, notable gaps in the literature are listed below:

- To date, no study has employed the PPF-WENSLO and PPF-COPRAS methods.
- There is no research integrating ML techniques with MCDM approaches for the selection of blockchain technologies in the healthcare sector.
- Similarly, no investigation has aimed to reduce redundant and overlapping criteria using ML-based methods in the context of blockchain platform selection within healthcare.

### *2.4. Contributions*

I. Developing an efficient decision support model that helps healthcare institutions evaluate and select blockchain technologies more transparently and effectively,
II. Modeling the evaluation process by using AHC to merge overlapping criteria into more meaningful and coherent groups, reducing redundancy through an ML-based refinement step,
III. Offering a methodological innovation by integrating PPFSs with the WENSLO and COPRAS methods for the first time, handling uncertainty while supporting objective weighting and transparent ranking,
IV. Providing a comparative assessment of widely used healthcare-oriented blockchain platforms, offering practical insights that help DMs understand the strengths and weaknesses of alternative technologies,
V. Presenting an adaptable and scalable decision-making framework that can be reused in other technology selection problems beyond healthcare, making the model valuable not only for researchers but also for practitioners seeking flexible evaluation tools.

## 3. The proposed framework

In this study, a mixed method, as an integration of ML and MCDM methods, is developed. According to this integrated method, firstly, the AHC method is applied to reduce the criteria found in the literature, then WENSLO, based on PPFSs is used to determine the weights on the determined criteria, and the COPRAS method based on PPFSs, is utilized to rank the alternatives.

This section introduces a new decision support model, PPF-WENSLO-COPRAS, which combines the WENSLO and COPRAS methods within the PPFSs framework. This hybrid method addresses uncertainty and imprecision in expert evaluations by facilitating a more accurate fuzzy set. It does so by obtaining relative proportional values for the membership function parameters instead of asking experts to provide precise decimal estimates for them. The proposed method utilizes WENSLO to evaluate the subjective significance of criteria. The COPRAS method is employed to rank and select alternatives when DMs require a transparent, weight-sensitive ranking approach that accommodates mixed-type criteria and is straightforward for stakeholders to understand. Fig. 1 illustrates the flowchart of the proposed PPF-WENSLO-COPRAS method, which is detailed in the subsequent steps.

### *3.1. Agglomerative hierarchical clustering*

The AHC algorithm, induced from the similarity matrix developed based on literature co-occurrence frequency, has been utilized to reduce the number of criteria. This algorithm clusters similar criteria, and a representative criterion is selected from each cluster to facilitate a rigorous and coherent selection process.

Having numerous criteria creates evaluation difficulties in decision-making and prolongs the analysis time. Therefore, it is essential to select appropriate features (criteria) to simplify the decision model. In this study, the frequency of occurrence in literature is utilized to assess the similarity among the criteria, and the AHC technique is applied based on these frequencies. This approach aims to eliminate redundant or low-contribution criteria by clustering similar criteria and identifying representative ones. The execution mechanism of the AHC is described below:

**Step 1.** Start from a set of candidates obtained from the literature to determine the frequency of the criteria.

**Step 2:** Compute a co-occurrence frequency for each pair of criteria, representing how many studies include both criteria, and consider it as a similarity indicator.

**Step 3:** As AHC operates on distances rather than similarities, we turn co-occurrence frequencies into distances. The distance of each pair of criteria was calculated based on the subtraction of the current frequency from the maximum one. The idea is that frequently co-occurrent criteria have small distances, and rarely co-occurrent criteria have large distances.

**Step 4:** AHC with Ward's linkage is applied to the distance matrix. Ward's method merges clusters so that at every step, the increase in within-cluster variance is minimized; this leads to compact, internally homogeneous groups of criteria (Strauss and Von Maltitz, 2017).

**Step 5:** Present the results as a dendrogram and describe the selection of the final number of clusters, which in this study is done by analyzing height, focusing on early merges (highly similar ones), and preserving conceptual coherence, such as the "technical performance", "system continuity", and "accessibility" clusters.

These elements enhance the transparency of the model's ML component, while also emphasizing that AHC functions as a data-driven mechanism for reducing features or criteria. The resulting output is subsequently integrated into the PPFS-based MCDM stage. The pseudo-code of the AHC is also given by Algorithm 1.

**Algorithm 1: Pseudo-Code of the AHC**

// Step 1: Data Preparation
**1.** Input: Set of criteria $C = \{c_1, c_2, ..., c_n\}$
**2.** Calculate Co-occurrence Frequency Matrix ($F$):
$F(i, j)$ = Frequency of co-occurrence of criteria $c_i$ and $c_j$ in the literature.
**3.** Determine Maximum Frequency: $F_{max} = \max(F)$
**4.** Calculate Distance Matrix ($D$):
$D(i, j) = F_{max} - F(i, j)$ // Distance is inverse of similarity
// Step 2: AHC (Ward's Linkage)
**5.** Initialization: Start with n clusters, where each criterion $c_i$ is its own cluster $C_i$.
**6.** Loop until only one cluster remains ($C_{all}$):
6.1. Identify the two clusters ($C_a$, $C_b$) that, when merged, result in the minimum increase in the total within-cluster variance (Ward's criterion)
6.2. Merge $C_a$, $C_b$ into a new cluster $C_{new}$.
6.3. Update the distance matrix $D$ to include $C_{new}$ (using the new variance-minimizing distance).
**7.** Store the merging sequence and distances to generate the Dendrogram
// Step 3: Criteria Selection
**8.** Analyze the Dendrogram: Determine the cut-off point (or desired number of clusters) that reveals conceptually meaningful clusters (Cluster1 to Cluster8).
**9.** Selection: For each final cluster ($Cluster_k$), select one representative criterion based on metrics like highest literature frequency, ease of application, and conceptual comprehensiveness.
**10.** Output: Reduced set of representative criteria ($C' \subset C$) for MCDM.

One of the main reasons why AHC has been preferred within this study is that it does not require the number of clusters to be predetermined and allows the detection of natural clusters from data. Algorithms such as k-

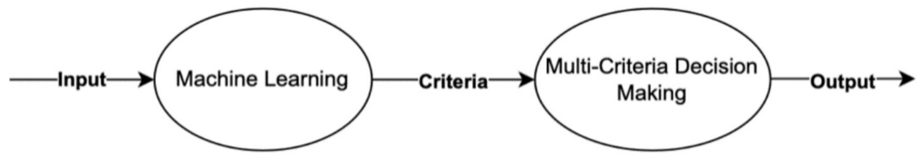


**Fig. 1.** Methodological framework.

means, on the other hand, are based solely on numeric distance, are initially sensitive, and do not possess interpretability. On the other hand, the AHC method always returns the same result with the same data because of its deterministic nature, and gives DMs a good visual analysis opportunity because of the dendrogram (Toi et al., 2022). Because of these features, AHC distinguishes itself from the other clustering methods in this research by providing more meaningful, flexible, and interpretable criteria selection mechanisms.

### 3.2. Preliminaries of PPFSs

**Definition 1.** (*The PPFSs, represented by A, is defined by Eq. (1) (Kahraman, 2024):*)

$$A = \{\langle x;\ \mu(x),\ \pi(x),\ \vartheta(x)\rangle | x \in X\}. \tag{1}$$

In this case, every element in the universal set $X$ is linked to a tuple $\mu(x), \pi(x), \vartheta(x)$, where $\mu(x)$ denotes the degree of positive membership, $\pi(x)$ denotes the degree of neutral membership, and $\vartheta(x)$ denotes the degree of negative membership.

The expert judges the proportions between in Eqs. (2)-(3):

$$\mu(x) = k_1 \pi(x), \tag{2}$$

$$\vartheta(x) = k_2 \pi(x), \quad \text{satisfying } \pi(x) + k_1 \pi(x) + k_2 \pi(x) \le 1, \tag{3}$$

and

$$\pi(x) \le \frac{1}{1 + k_1 + k_2}. \tag{4}$$

Eq. (5) denotes the degree of refusal for a given element $x$:

$$r(x) = 1 - (\pi(x) + k_1 \pi(x) + k_2 \pi(x)). \tag{5}$$

The definition for the neutral membership degree $\pi(x)$ is as Eq. (6):

$$\pi(x) = \frac{1 - r(x)}{1 + k_1 + k_2}. \tag{6}$$

Then, each element in the set $A$ can be represented as

$$A = \left\{ \langle x; k_1 \frac{1 - r(x)}{1 + k_1 + k_2}, \frac{1 - r(x)}{1 + k_1 + k_2}, k_2 \frac{1 - r(x)}{1 + k_1 + k_2} \rangle | x \in X \right\}. \tag{7}$$

Hence, Eq. (8) can be used to characterize PPFSs:

$$A = \{\langle x; k_{\pi 1}, k_{\pi 2}\rangle | x \in X\}. \tag{8}$$

**Definition 2.** (*Let* $A = \{\langle x; k_{\pi A1}, k_{\pi A2}\rangle | x \in X\}$ *and* $B = \{\langle x; k_{\pi B1}, k_{\pi B2}\rangle | x \in X\}$ *be two Proportional Picture Fuzzy Numbers (PPFNs) and* $\lambda > 0$*. Some mathematical operations are given in Eqs. (9)-(10):*)

$$\begin{aligned} A + B = \Bigg( & x, k_{A1}\frac{1 - r_A(x)}{1 + k_{A1} + k_{A2}} + k_{B1}\frac{1 - r_B(x)}{1 + k_{B1} + k_{B2}} - k_{A1}\frac{1 - r_A(x)}{1 + k_{A1} + k_{A2}} \\ & \times k_{B1}\frac{1 - r_B(x)}{1 + k_{B1} + k_{B2}}, \frac{1 - r_A(x)}{1 + k_{A1} + k_{A2}} \times \frac{1 - r_B(x)}{1 + k_{B1} + k_{B2}}, k_{B2}\frac{1 - r_B(x)}{1 + k_{B1} + k_{B2}} \\ & \times k_{A2}\frac{1 - r_A(x)}{1 + k_{A1} + k_{A2}}, x \in X \Bigg), \end{aligned} \tag{9}$$

$$\begin{aligned} A \times B = \Bigg( & x, k_{A1}\frac{1 - r_A(x)}{1 + k_{A1} + k_{A2}} \times k_{B1}\frac{1 - r_B(x)}{1 + k_{B1} + k_{B2}}, \frac{1 - r_A(x)}{1 + k_{A1} + k_{A2}} + \frac{1 - r_B(x)}{1 + k_{B1} + k_{B2}} - \frac{1 - r_A(x)}{1 + k_{A1} + k_{A2}} \times \frac{1 - r_B(x)}{1 + k_{B1} + k_{B2}}, k_{B2}\frac{1 - r_B(x)}{1 + k_{B1} + k_{B2}} \\ & + k_{A2}\frac{1 - r_A(x)}{1 + k_{A1} + k_{A2}} - k_{B2}\frac{1 - r_B(x)}{1 + k_{B1} + k_{B2}} \times k_{A2}\frac{1 - r_A(x)}{1 + k_{A1} + k_{A2}}, x \in X \Bigg). \end{aligned} \tag{10}$$

**Definition 3.** (*The score function defined in Eq. (11) is employed to derive the crisp numbers of evaluation matrices. According to Eq. (11), when the computation yields a positive outcome in the first row, the procedure continues with the first row; conversely, if a negative outcome is obtained, the evaluation proceeds with the second row.*)

$$S(k_{\pi 1}, k_{\pi 2}) = \begin{cases} 10 \times \left( k_{\pi 1}\frac{1}{1 + k_{\pi 1} + k_{\pi 2}} - \left( \frac{k_{\pi 1}}{1 + k_{\pi 1} + k_{\pi 2}} \right) \Big/ 2 - k_{\pi 2}\frac{1}{1 + k_{\pi 1} + k_{\pi 2}} \right), & \text{if positive}, \\ \frac{1}{10} \times \left( k_{\pi 2}\frac{1}{1 + k_{\pi 1} + k_{\pi 2}} - \left( \frac{k_{\pi 1}}{1 + k_{\pi 1} + k_{\pi 2}} \right) \Big/ 2 - k_{\pi 1}\frac{1}{1 + k_{\pi 1} + k_{\pi 2}} \right), & \text{otherwise}. \end{cases} \tag{11}$$

### 3.3. PPF-WENSLO-COPRAS model

**Step 1:** Problem definition

The PPF-WENSLO-COPRAS method is utilized to address MCDM problems that involve a set of alternatives $\text{ค}_j = \{\text{ค}_1, \text{ค}_2, \cdots, \text{ค}_m\}$ assessed against a series of criteria $\text{อ}_i = \{\text{อ}_1, \text{อ}_2, \cdots, \text{อ}_n\}$ by $t$ experts $\ddagger_t = \{\ddagger_1, \ddagger_2, \cdots, \ddagger_t\}$. Each criterion $\text{อ}_i$ is assigned a weight $w_i$, which reflects its relative importance, such that $\sum_{i=1}^{n} w_i$. The performance of each alternative $\text{ค}_j$ under criterion $\text{อ}_i$ and the importance of the criteria is represented using PPFNs.

**Step 2:** Compute criteria weights using PPF-WENSLO.

The WENSLO is a novel approach aimed at objectively determining the criteria weights in MCDM procedures. The technique allows weights to be calculated without the need for subjective DM preferences, using envelope and slope values obtained from the data of each criterion (Pamucar et al., 2023). One of the greatest advantages of WENSLO is that the criteria do not affect the calculation process regardless of whether they are of benefit- or cost-type; thus, the method provides a consistent and solid structure (Pamucar et al. 2023). Additionally, through a cumulative analysis of normalized criteria data, randomness in the data is removed, and the behavioral tendency of the criteria is revealed more accurately, allowing one to derive more reliable weight values (Pamucar et al., 2023). The WENSLO method can be easily adapted to different areas, and thanks to its dynamic structure, it can produce reliable results even in environments containing uncertainty (Demir, 2025). This method has eight steps as follows (Gopisetty & Sama, 2025; Pamucar et al., 2023):

*Sub-step* 2.1: Each expert ($\ddagger_t$) assesses the significance levels of the criteria utilizing linguistic phrases. The designated importance levels are subsequently transformed into PPFNs, creating the criteria evaluation matrix ($\widetilde{\pounds}$) as in Eq. (12):

$$\widetilde{\pounds} = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & & e_{2n} \\ \vdots & & \ddots & \vdots \\ e_{t1} & e_{t2} & \cdots & e_{tn} \end{bmatrix}, \tag{12}$$

where $e_{ti}$ is the evaluation of criterion $\text{อ}_i$ by expert $\ddagger_t$, expressed as a PPFNs, and defined as $e_{ti} = (k_{\pi 1}, k_{\pi 2})$.

*Sub-step* 2.2: Employ the score function presented in Eq. (13) to determine the crisp value for each criterion utilizing the PPFNs derived from the decision matrix:

$$S(k_{\pi 1}, k_{\pi 2}) = \begin{cases} 10 \times \left( k_{11n}\dfrac{1}{1+k_{11n}+k_{21n}} - \dfrac{\left(k_{11n}\dfrac{1}{1+k_{11n}+k_{21n}}\right)}{2} - k_{21n}\dfrac{1}{1+k_{11n}+k_{21n}} \right), & \text{if} \quad \text{positive}, \\ 1 \Big/ \left( 10 \times k_{21n}\dfrac{1}{1+k_{11n}+k_{21n}} - \left(k_{11n}\dfrac{1}{1+k_{11n}+k_{21n}}\right) \Big/ 2 - k_{11n}\dfrac{1}{1+k_{11n}+k_{21n}} \right), & \text{otherwise}. \end{cases} \tag{13}$$

*Sub-step* 2.3: After obtaining the crisp decision matrix, transform the decision matrix into a complex multidimensional space with Eq. (14):

$$z_{ij} = \frac{\zeta_{ij}}{\sum_{i=1}^{m}\zeta_{ij}} \quad \forall j \in \left\{1, 2, \cdots, n\right\}. \tag{14}$$

*Sub-step* 2.4: Determine the class ranges for the criteria via Eq. (15):

$$\Delta z_j = \frac{\max z_{ij} - \min z_{ij}}{1 + 3.322 \times \log(m)} \quad \forall j \in \left\{1, 2, \cdots, n\right\}. \tag{15}$$

*Sub-step* 2.5: Calculate the criteria envelope with given Eq. (16):

$$E_j = \sum_{i=1}^{m-1} \sqrt{\left(z_{i+1,j} - z_{i,j}\right)^2 + \Delta z_j^{\,2}} \quad \forall j \in \left\{1, 2, \cdots, n\right\}. \tag{16}$$

*Sub-step* 2.6: Calculate the variation between alternatives and scales by using Eq. (17):

$$tan\varphi_j = \frac{\sum_{i=1}^{m} z_{ij}}{(m-1)\Delta z_j} \quad \forall j \in \left\{1, 2, \cdots, n\right\}. \tag{17}$$

*Sub-step* 2.7: Calculate the new value defined to capture both the spatial distribution and sensitivity within the decision matrix via Eq. (18):

$$q_j = \frac{E_j}{tan\varphi_j} \quad \forall j \in \left\{1, 2, \cdots, n\right\}. \tag{18}$$

*Sub-step* 2.8: Calculate the total envelope slope by using Eq. (19). This ensures that the alternatives receive an objective and distinct weight that reflects their relative importance within the overall decision matrix.

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \quad \forall j \in \left\{1, 2, \cdots, n\right\}. \tag{19}$$

**Step 3:** Compute alternatives ranking using PPF-COPRAS

COPRAS offers an approach to determine the relative priorities and the level of benefits of the alternatives of MCDM problems in a structured manner (Mousavi-Nasab and Sotoudeh-Anvari, 2017; Zavadskas et al., 1994). In the COPRAS method, the best overall performance of the alternatives is determined by considering both the benefit criteria that should be maximized and the cost criteria that should be minimized, and the relative importance value of each alternative is determined. The COPRAS technique is widely employed in engineering and management applications owing to its advantages, including computational simplicity, direct incorporation of criteria weights, and the provision of clear and easily interpretable rankings for DMs (Patil et al., 2022). The calculation procedure is as follows (Chatterjee et al., 2011; Mousavi-Nasab and Sotoudeh-Anvari, 2017):

*Sub-step* 3.1: To ascertain the expert weights, the expertise levels of the experts are initially evaluated by themselves using linguistic terms in Table 3.

*Sub-step* 3.2: The expertise level matrix, expressed as PPFNs, is transformed into precise values utilizing the score function outlined in Eq. (11).

*Sub-step* 3.3: The expert weights are derived through the application of the linear normalization, which divides each value by the sum of all values, yielding the expert weight vector.

*Sub-step* 3.4: Each expert assessed each alternative according to the criteria outlined in Table 9, utilizing the specified linguistic expressions.

The decision matrix $\zeta$ is constructed as follows:

$$\zeta^t = \begin{bmatrix} \zeta_{11}^1 & \zeta_{12}^1 & \cdots & \zeta_{1n}^1 \\ \zeta_{11}^2 & \zeta_{22}^2 & & \zeta_{2n}^2 \\ \vdots & & \ddots & \vdots \\ \zeta_{m1}^t & \zeta_{m2}^t & \cdots & \zeta_{mn}^t \end{bmatrix}, \tag{20}$$

where $\zeta_{ij}^t$ represents the performance of alternative ฅ$_j$ under criterion $\vartheta_i$ given by expert $‡_t$.

*Sub-step* 3.5: The identified assessments are subsequently transformed into PPFNs, establishing the initial decision matrix. The aggregated decision matrix is derived through the application of the proportional picture fuzzy weighted averaging (PPFWA) aggregation operator calculation, as outlined in Eq. (21):

$$PPFWA_w(\alpha_1, \alpha_2, \cdots, \alpha_n) = \left(1 - \prod_{j=1}^{n}\left(1 - k_{1j}\frac{1}{1+k_{1j}+k_{2j}}\right)^{w_j}, \prod_{j=1}^{n}\left(\frac{1}{1+k_{1j}+k_{2j}}\right)^{w_j}, \prod_{j=1}^{n}\left(k_{2j}\frac{1}{1+k_{1j}+k_{2j}}\right)^{w_j}\right), \tag{21}$$

where $\alpha_j \quad (j = 1, 2, \cdots, n)$ is a collection of PPFNs.

*Sub-step* 3.6: The aggregated decision matrix, expressed as picture fuzzy numbers, is transformed into crisp values utilizing the score function outlined in Eq. (22)

$$S_i = \mu_{G_i} + \frac{\eta_{G_i}}{2} + \frac{v_{G_i}}{2}\left(1 + \mu_{G_i} - v_{G_i}\right) \quad (i = 1, 2, \cdots, m). \tag{22}$$

*Sub-step* 3.7: Normalize the decision matrix using Eq. (23):

$$rij = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (i = 1, 2, \cdots, m; j = 1, 2, \cdots, n), \tag{23}$$

where $x_{ij}$ is the raw (original) value of the $j^{th}$ criterion for the $i^{th}$ alternative.

*Sub-step* 3.8: Weight normalized matrix using Eq. (24):

$$y_{ij} = w_j \times r_{ij} \quad (i = 1, 2, \cdots, m; j = 1, 2, \cdots, n), \tag{24}$$

where $w_j$ represents the weight of the criteria.

*Sub-step* 3.9: Utilizing Eqs. (25) and (26), compute the sums of weight-normalized scores for both cost and benefit criteria as follows:

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \quad \left(i = 1, 2, \cdots, m\right), \tag{25}$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \quad \left(i = 1, 2, \cdots, m\right). \tag{26}$$

Here, $S_{+i}$ represents the score that the alternative collects from the benefit criteria, while $S_{-i}$ represents the total weight that the alternative receives from the disadvantageous criteria.

*Sub-step* 3.10: With the help of Eq. (27), determine the alternatives' relative importance as follows:

$$Q_i = S_{+i} + \frac{\sum_{i=1}^{m} S_{-i}}{S_{-i}\sum_{i=1}^{m}\frac{1}{S_{-i}}} \quad (i = 1, 2, \cdots, m), \tag{27}$$

where $Q_i$ value is the relative significance of each alternative and is used to determine the overall ranking of the alternatives.

*Sub-step* 3.11: Calculate the alternative's performance level $U_i$:

$$U_i = \frac{Q_i}{Q_{max}} \times 100 \quad (i = 1, 2, \cdots, m). \tag{28}$$

Here, $Q_{max}$ is the highest value among all alternatives.

## 4. Case study

The selection of blockchain technology working in the healthcare system was investigated in this study. A ranking was established among the various alternatives from the application areas after the criteria that are significant in this selection were examined from the body of existing literature. Additionally, because there were so many criteria, the AHC method was implemented to simplify the process so that viewers can more clearly communicate their ideas. In the implementation of this study, six DMs were selected. These DMs have at least 10 years of work experience and are experts in their fields. The expertise levels of experts are found as $(0.20, 0.20, 0.15, 0.15, 0.15, 0.15)$. Interviews were conducted with these selected DMs, and the relevant forms were filled out in this way.

The study's criteria and alternatives are thoroughly described under this section, followed by an expression of the findings from the relevant techniques applied to the application.

### 4.1. Determination of the criteria

In the selection of blockchain technologies in the healthcare industry, considerations made in the evaluation of technologies reflect technical as well as operational needs. The relevant criteria were identified through extensive literature review. These criteria are: *Security, Cost, Integration, Performance, Privacy, Scalability, Trust, Efficiency, Transparency, Reliability, Accessibility, Usability, Energy, Flexibility, Latency, Decentralization, Accuracy, Availability, Complexity, Interoperability* (Bankuoru Egala et al., 2023; Chakraborty et al., 2023; Demir, 2025; Erol et al., 2023; Gardas et al., 2022; Khan and Ali, 2022; S. Khan et al., 2023; Krishankumar et al., 2024; Liu et al., 2024; Mishra et al., 2023; Qahtan et al., 2022; Zarour et al., 2020).

Security, privacy, reliability, accessibility, and accuracy are the most critical among them. Since health information is extremely sensitive, the blockchain framework must be secure from external attacks, patient information must not be accessible externally, and data must be processed and stored correctly (Ali et al., 2021). Privacy encompasses not only technical encryption but also access protocols designed to safeguard patient confidentiality. Reliability and accessibility imply that the system must operate continuously and maintain high fault tolerance. Conversely, efficiency and cost are critical considerations for healthcare institutions during implementation. A blockchain system should offer low-cost installation and maintenance while ensuring operational efficiency, including high transaction throughput and optimized energy consumption (Sharma, 2018). Energy consumption is an important consideration, particularly for environmental sustainability in healthcare systems managing large volumes of data. Latency is equally critical in contexts requiring real-time data flow, as the system's responsiveness directly affects patient safety. Additional criteria, such as integration and flexibility, reflect the system's ability to operate seamlessly with existing health informatics infrastructures and its scalability to accommodate evolving requirements (Jameil and Al-Raweshidy, 2024). Usability encompasses not only the intuitiveness of the software interface but also the ease with which healthcare personnel can learn to operate the system. Trust and openness give both patients and health professionals the assurance to use the system without fear. Decentralization specifically allows health information to be shared securely without being under the umbrella of one power (Usman and Qamar, 2020). When all of these demands are evaluated as a whole, it becomes apparent that blockchain technology should not only be a technical solution in the healthcare industry but also a multi-aspect system meeting ethical, legal, and functional requirements.

### 4.2. Determination of the alternatives

In this study, five leading blockchain platforms were selected due to their frequent use in healthcare pilot projects and their strong presence in the academic literature. Instead of offering a comprehensive technical review, our focus is directed toward the aspects most relevant to healthcare applications, namely, their consensus mechanisms, privacy features, and interoperability capabilities:

***(1) Hyperledger Fabric***

Hyperledger Fabric is an open source blockchain platform to facilitate secure, efficient data management within the healthcare sector. With its private mode, only verified members can have access to the system, presenting a true godsend in case of keeping patient information secret and secure. This system, by facilitating that a secure communication network can be established between hospitals, healthcare establishments, insurers, and patients, ensures the integrity of the information, as well as ensuring that the information is traceable (Yaqoob et al., 2022).

Confidential information, including patient history, treatment records, and insurance details, can be securely stored and shared with authorized parties on a need-to-know basis. One of the key contributions of Hyperledger Fabric in healthcare is its capacity to prevent fraudulent insurance claims and automate verification processes. For instance, when a patient is admitted to a hospital, their prior data can be securely transmitted to the insurance provider, enabling timely and secure payments. Simultaneously, the system identifies suspicious claims, thereby reducing the risk of fraud (Jena et al., 2024).

***(2) Ethereum***

Ethereum is an open-source, blockchain-based platform for safe, transparent, and decentralized data management in healthcare. Although open to everyone by virtue of its permissionless nature, it could be used with some encryption and identity management technologies to maintain the confidentiality of personal health information. With the help of the smart contracts offered by Ethereum, health data such as patient information, laboratory tests, and prescription records can be automatically recorded and sent to interested parties based on predetermined rules (Chenthara et al., 2020). The system offers a trust-based and traceable communication platform among patients, doctors, and insurance companies. At the same time, as a result of Ethereum-based solutions, patients' data is registered in an immutable manner, preventing medical mistakes and making transparent tracking of treatment history easier.

Furthermore, health data sharing is conducted with the patient's consent, ensuring that full ownership of the data remains in the patient's control. This approach enhances the protection of patient privacy, accelerates the data-sharing process, and contributes to improving the quality of healthcare services (Das and Viswanathan, 2023).

***(3) Corda***

Corda is a distinct (permissioned) blockchain technology used in the healthcare sector and is differentiated by the advantages it has to provide, especially with regard to privacy, data integrity, and security. Given the nature of health data being sensitive in character, the technology facilitates direct and secure sharing of data between only the relevant parties. This feature of Corda enables safe sharing of patient data among different hospitals, labs, and clinics (Hasan et al., 2022). For example, the care history of a patient that has been received from various healthcare organizations can be made accessible to all such organizations on a decentralized basis, but with consent, owing to the Corda network. This speeds up the process of diagnosis and treatment, especially in emergency situations, and eliminates data loss. Unlike conventional blockchains, Corda does not send all information to all nodes in the network. Therefore, data privacy is guaranteed as well as system performance. Because of this architecture in the healthcare industry, for example, only the involved doctor, nurse, or medical facility can see specific data about the patient.

***(4) Algorand***

Algorand is an advanced blockchain platform particularly suitable for the healthcare sector, especially in telemedicine, where ensuring data integrity and security is critical. Telemedicine platforms must manage patient information electronically while delivering healthcare services to remote patients. In the process, manipulation of data, unauthorized access, and privacy violations are matters of utmost concern (Alrebh et al., 2024). With the structural elements offered by Algorand, patient information is stored on the blockchain in an unchangeable form. Particularly, Algorand Smart Contracts (ASCIs) allow patients to remain fully in charge of their data; patients assent or refuse specifically who will view this information. The two-layer private blockchain architecture of Algorand, known as "co-chain", offers security and availability of health data proportionately. In this model, public layer communication is possible, yet sensitive data are kept in the private layer alone. This way allows the system to provide transparency as well as patient privacy concurrently. This model also grants institutions a choice of validators and an option to gain more control over the system.

***(5) Medicalchain***

Medicalchain is an architecture that embeds blockchain technology into medicine, and the core goal of this is to ensure patient information is treated in an open, secure, and controllable manner. In this context, patients retain ownership of their health information, meaning they directly control who can access their data, for what purposes, and for how long (Leonard and Wiljer, 2007). This approach helps safeguard patient confidentiality and data protection. Medicalchain functions as an intermediary among hospitals, physicians, laboratories, and other healthcare providers, ensuring that health data remains centralized and intact. For example, when a patient registers in several healthcare facilities within various cities or countries, all his or her data are saved securely in a decentralized form because of Medicalchain and can be accessed by certified healthcare professionals. This is very convenient as far as obtaining the patient's history information instantly is concerned, especially in cases of emergencies. The platform also allows remote healthcare services. Doctors can see historical medical data from patients via Medicalchain, carry out video consultations, and make diagnoses (Alshbatat and Awawdeh, 2024). These eliminate the issues of time and space, which enable access to healthcare. Secondly, since the data are encrypted on the blockchain, it is impossible to amend or delete the data, and thus makes records more trustworthy. Thus, Medicalchain aims to create a more open, fast, and secure environment for the health industry professionals, and patients alike through a patient-centered model of healthcare.

The hierarchal structure of the decision-making problem is displayed by Fig. 2.

### 4.3. Results of the AHC method

In the process of reducing the criteria, only one representative criterion is selected from each cluster, as presented in Table 2 and illustrated in Fig. 3. During the selection of representatives, factors such as the frequency of occurrence in literature, ease of application, measurability, and conceptual comprehensiveness are considered. Consequently, the initial set of 20 criteria is refined to eight representative criteria, ensuring minimal loss of information. This technique provides a methodical and comprehensible reduction process from literature, but maintains the model less complex. This process, allowing the exploration of the relationship between criteria based not only on numerical data but also on meaning conceptualization, can be considered a strong pre-processing method within decision support systems. Following the

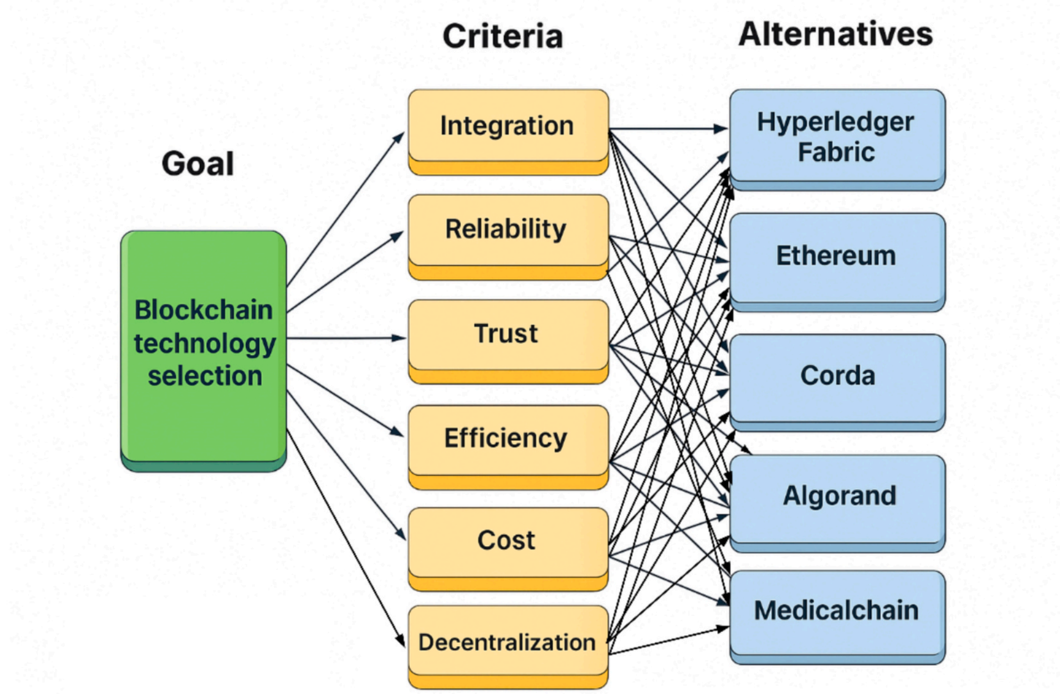


**Fig. 2.** Hierarchical representation of the criteria and alternatives.

**Table 2**
Clustered and selected criteria.

| Cluster | Criteria | Reason | Selected Criteria |
|---|---|---|---|
| $Cluster_1$ | Integration, performance, privacy, energy | Combined at an early stage, representing the technical performance group | Integration |
| $Cluster_2$ | Reliability, availability | Combined early and representing the system continuity group | Reliability |
| $Cluster_3$ | Trust, accuracy, complexity | Grouped based on trust and accuracy, reflecting a common context | Trust |
| $Cluster_4$ | Scalability, efficiency, transparency | Represents system capacity and operational efficiency | Efficiency |
| $Cluster_5$ | Accessibility, latency, usability | Combined most recently, reflecting the accessibility context | Accessibility |
| $Cluster_6$ | Security, cost | Combined at a later stage, focusing on cost considerations | Cost |
| $Cluster_7$ | Flexibility | Considered independently as a standalone criterion | Flexibility |
| $Cluster_8$ | Interoperability, decentralization | Reflects a cohesive distributed system structure | Decentralization |

**Table 3**
Linguistic scale for evaluation of criteria.

| Linguistic Terms | Proportions $(k_{\pi 1}, k_{\pi 2})$ |
|---|---|
| Certainly low | (1, 7) |
| Very low | (2, 6) |
| Low | (5, 3) |
| High | (3, 5) |
| Very high | (6, 2) |
| Certainly high | (7, 1) |

grouping process, an expert selects a representative criterion from each group to ensure a robust and meaningful evaluation.

### 4.4. Results of the PPF-WENSLO

The first stage of the decision-making model involves determining the weights of the criteria. For this purpose, the PPF-WENSLO method is applied in this study. First, DMs are interviewed according to the linguistic terms given in Table 3, and scoring tables are obtained as seen in Table 4.

According to the evaluations specified in Table 4, the initial matrix is created as given in Table 5.

This decision matrix is normalized according to the formulation in Eq. (12), and this normalized matrix is given in Table 6.

Then, the class ranges, envelope, and tangent values are calculated for the criteria using Eqs. (15)-(17), as given in Table 7.

Moreover, the final weights are computed using Eqs. (18)-(19). Therefore, the final weights are obtained as given in Table 8.

### 4.5. Results of the PPF-COPRAS

After finding the weights for the determined criteria, in the second stage, the alternatives need to be evaluated according to the linguistic terms specified in Table 9, specific to the criteria.

The assessments of alternatives using Table 9 are outlined in Table A.1 (Appendix). Accordingly, the initial decision matrix is created, and this decision matrix is displayed in Table 10.

Then, this decision matrix is normalized using the formulations given in Eq. (23), and this normalized matrix is given in Table 11.

Afterwards, the relative significance values for each alternative are determined using Eqs. (25)-(27), and these values are outlined in Table 12.

Finally, performance levels for each alternative are found using Eq. (28) and ranked according to these performance levels. These results are illustrated in Table 13.

Although the values in Table 13 are less than 0.001 apart, within the PPF-COPRAS structure, such differences become meaningful. Since

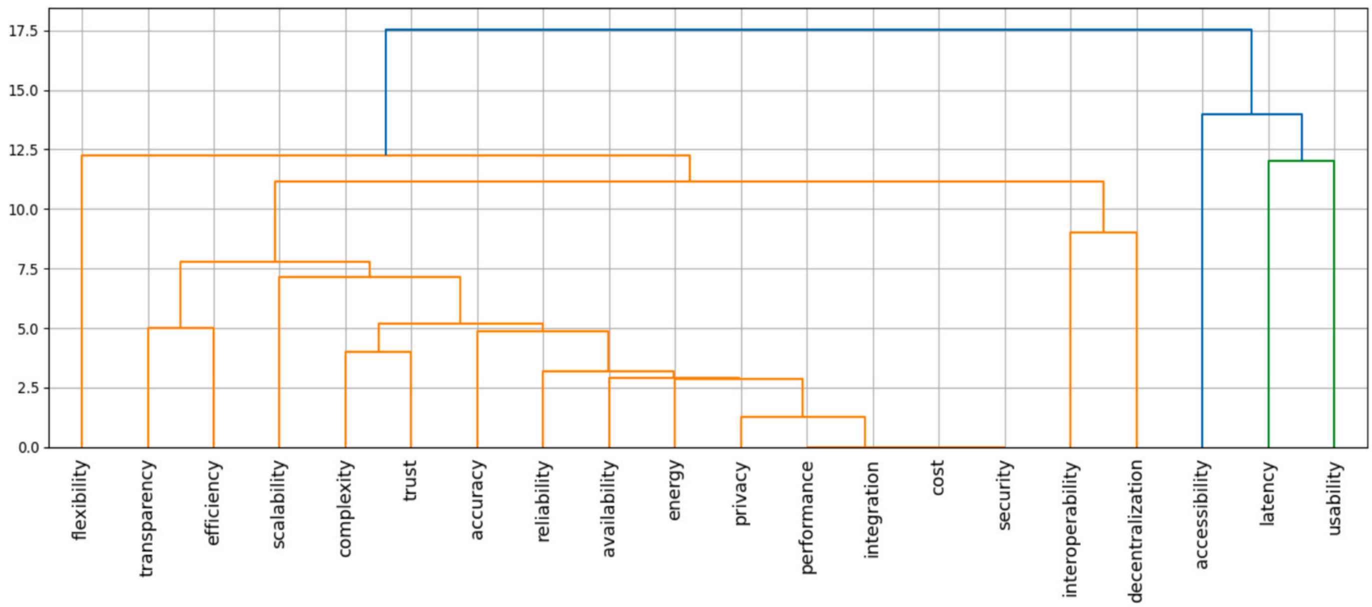


**Fig. 3.** Dendrogram of the AHC Method.

**Table 4**
Criteria assessment by the DMs.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|---|---|---|---|---|---|---|---|---|
| **DM1** | Very low | Very low | Low | Certainly low | High | Very low | Certainly low | Low |
| **DM2** | Low | Very low | Low | High | Low | Low | Certainly high | Low |
| **DM3** | Low | Certainly low | Low | Very low | Low | Very high | High | Very low |
| **DM4** | Very high | High | Very low | Very low | Very high | Very low | Low | High |
| **DM5** | Very high | High | Low | High | Very high | Certainly low | High | Certainly low |
| **DM6** | Very low | Certainly low | Certainly low | Very high | Very low | Very low | Very low | Certainly high |

**Table 5**
Decision matrix.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|---|---|---|---|---|---|---|---|---|
| **DM1** | 3.888 | 3.888 | 1.666 | 6.111 | 0.600 | 3.888 | 3.888 | 1.666 |
| **DM2** | 1.666 | 3.888 | 1.666 | 0.600 | 1.666 | 1.666 | 0.163 | 1.666 |
| **DM3** | 1.666 | 6.111 | 1.666 | 3.888 | 1.666 | 0.257 | 0.600 | 3.888 |
| **DM4** | 0.257 | 0.600 | 3.888 | 3.888 | 0.257 | 3.888 | 1.666 | 0.600 |
| **DM5** | 0.257 | 0.600 | 1.666 | 0.600 | 0.257 | 6.111 | 0.600 | 6.111 |
| **DM6** | 3.888 | 6.111 | 6.111 | 0.257 | 3.888 | 3.888 | 3.888 | 0.163 |

**Table 6**
Normalized decision matrix.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|---|---|---|---|---|---|---|---|---|
| **DM1** | 0.335 | 0.183 | 0.100 | 0.398 | 0.072 | 0.197 | 0.360 | 0.118 |
| **DM2** | 0.143 | 0.183 | 0.100 | 0.039 | 0.200 | 0.085 | 0.015 | 0.118 |
| **DM3** | 0.143 | 0.288 | 0.100 | 0.253 | 0.200 | 0.013 | 0.056 | 0.276 |
| **DM4** | 0.022 | 0.028 | 0.233 | 0.253 | 0.031 | 0.197 | 0.154 | 0.043 |
| **DM5** | 0.022 | 0.028 | 0.100 | 0.039 | 0.031 | 0.310 | 0.056 | 0.434 |
| **DM6** | 0.335 | 0.288 | 0.367 | 0.017 | 0.466 | 0.197 | 0.360 | 0.012 |

**Table 7**
Values of the WENSLO method.

| Criteria | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|---|---|---|---|---|---|---|---|---|
| **Delta** | 0.087 | 0.072 | 0.074 | 0.106 | 0.121 | 0.082 | 0.096 | 0.117 |
| **Envelope** | 0.858 | 0.812 | 0.731 | 1.068 | 1.080 | 0.731 | 1.056 | 1.422 |
| **Tan** | 2.295 | 2.758 | 2.688 | 1.879 | 1.645 | 2.413 | 2.080 | 1.699 |

**Table 8**
Final weights of the criteria.

| Criteria | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|---|---|---|---|---|---|---|---|---|
| **Weights** | 0.098 | 0.077 | 0.071 | 0.149 | 0.1721 | 0.079 | 0.133 | 0.219 |

**Table 9**
Linguistic scale for the evaluation of the alternatives.

| Linguistic Terms | Proportions $(k_{\pi 1}, k_{\pi 2})$ |
|---|---|
| Certainly unsuitable | (1, 7) |
| Very unsuitable | (2, 6) |
| Unsuitable | (5, 3) |
| Suitable | (3, 5) |
| Very suitable | (6, 2) |
| Extremely suitable | (7, 1) |

COPRAS normalizes values relative to the best-performing alternative, when alternatives perform similarly on criteria, final performance levels will naturally converge toward 1.0000. As such, even small numerical gaps reflect tangible differences in aggregated weighted advantages and disadvantages.

To further investigate these differences, a rank index difference analysis which proposed to demonstrate differences for ranking results. For each alternative $A_j$, we compute $\Delta_j = Q_j - \min(Q_j)$. This amplifies small differences by showing how far each alternative is from the least-performing option in relative terms. The best-ranked alternative (ALT3) outperforms by 0.028 %, while ALT1 continues to outperform ALT2 by 0.021 %. While the actual magnitude of these differences is small, they are consistent and systematic across the criteria. The small margins are partly an artefact of the study design. As explained in Sub-section 4.2, the five alternatives were not random choices but had been pre-selected from the literature as the most implemented and widespread technologies in healthcare. Because of that, all five alternatives are inherently "strong" candidates.

### *4.6. Validation and sensitivity analysis*

This section validates the study's results through various scenarios in the sensitivity analysis. This study employed a three-stage process to evaluate the validity and reliability of the results. Consequently, this study initially investigates the impact of variations in criterion weight coefficients on the obtained solutions. The ranking results produced by different methods are then compared with those generated through the proposed approach.

#### *4.6.1. Sensitivity analysis of the criteria weights*

It is important to note that this sensitivity analysis is not just a quick validation; it involves developing 80 different scenarios. Therefore, the following are some key points:

- In fact, the resulting ranking reveals that Corda is the dominant solution for almost all scenarios, where the results remain stable even when the weights of the criteria change significantly.
- Ethereum, or ALT2, is generally the worst option in every case.
- The observed stability demonstrates that the objectively-derived data-driven PPF-WENSLO weights provide a robust tool for the decision model and further validate its underlying principle of excluding subjective judgments.

The study of weight coefficient fluctuations involves analyzing variations in the weight of each criterion to assess the influence of different conditions on alternatives. In a scenario analysis, eighty scenarios were developed, each featuring a 10 % decrease in the weight coefficients of the criteria, with the reduced amounts being equally redistributed to the weight coefficients of the remaining criteria. The sensitivity analysis yields 80 alternative scenarios, with results illustrated in Fig. 4.

The results presented in Fig. 4 indicate that, despite variations in all criteria weights, ALT3 remains the dominant solution within the

**Table 12**
Performance level and the ranking of the alternatives.

| Alternative | $Q_i$ |
|---|---|
| **ALT1** | 25.592 |
| **ALT2** | 25.571 |
| **ALT3** | 25.599 |
| **ALT4** | 25.575 |
| **ALT5** | 25.585 |

**Table 13**
Performance level and the ranking of the alternatives.

| Alternative | Performance level | Rank | $\Delta_j$ |
|---|---|---|---|
| **ALT1** | 0.9998 | 2 | 0.0210 |
| **ALT2** | 0.9989 | 5 | 0.0000 |
| **ALT3** | 1.0000 | 1 | 0.0280 |
| **ALT4** | 0.9991 | 4 | 0.0040 |
| **ALT5** | 0.9995 | 3 | 0.0140 |

**Table 10**
Decision matrix.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|---|---|---|---|---|---|---|---|---|
| **ALT1** | 0.593 | 0.536 | 0.534 | 0.680 | 0.494 | 0.590 | 0.673 | 0.655 |
| **ALT2** | 0.694 | 0.694 | 0.590 | 0.433 | 0.550 | 0.311 | 0.608 | 0.487 |
| **ALT3** | 0.688 | 0.414 | 0.710 | 0.562 | 0.713 | 0.614 | 0.640 | 0.575 |
| **ALT4** | 0.728 | 0.363 | 0.541 | 0.542 | 0.535 | 0.458 | 0.591 | 0.491 |
| **ALT5** | 0.685 | 0.529 | 0.611 | 0.542 | 0.420 | 0.670 | 0.609 | 0.703 |

**Table 11**
Normalized matrix.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|---|---|---|---|---|---|---|---|---|
| **ALT1** | 0.174 | 0.211 | 0.178 | 0.246 | 0.182 | 0.223 | 0.215 | 0.225 |
| **ALT2** | 0.204 | 0.273 | 0.197 | 0.156 | 0.202 | 0.117 | 0.194 | 0.167 |
| **ALT3** | 0.203 | 0.163 | 0.237 | 0.203 | 0.262 | 0.232 | 0.205 | 0.197 |
| **ALT4** | 0.214 | 0.143 | 0.181 | 0.196 | 0.197 | 0.173 | 0.189 | 0.168 |
| **ALT5** | 0.202 | 0.208 | 0.204 | 0.196 | 0.154 | 0.153 | 0.195 | 0.214 |

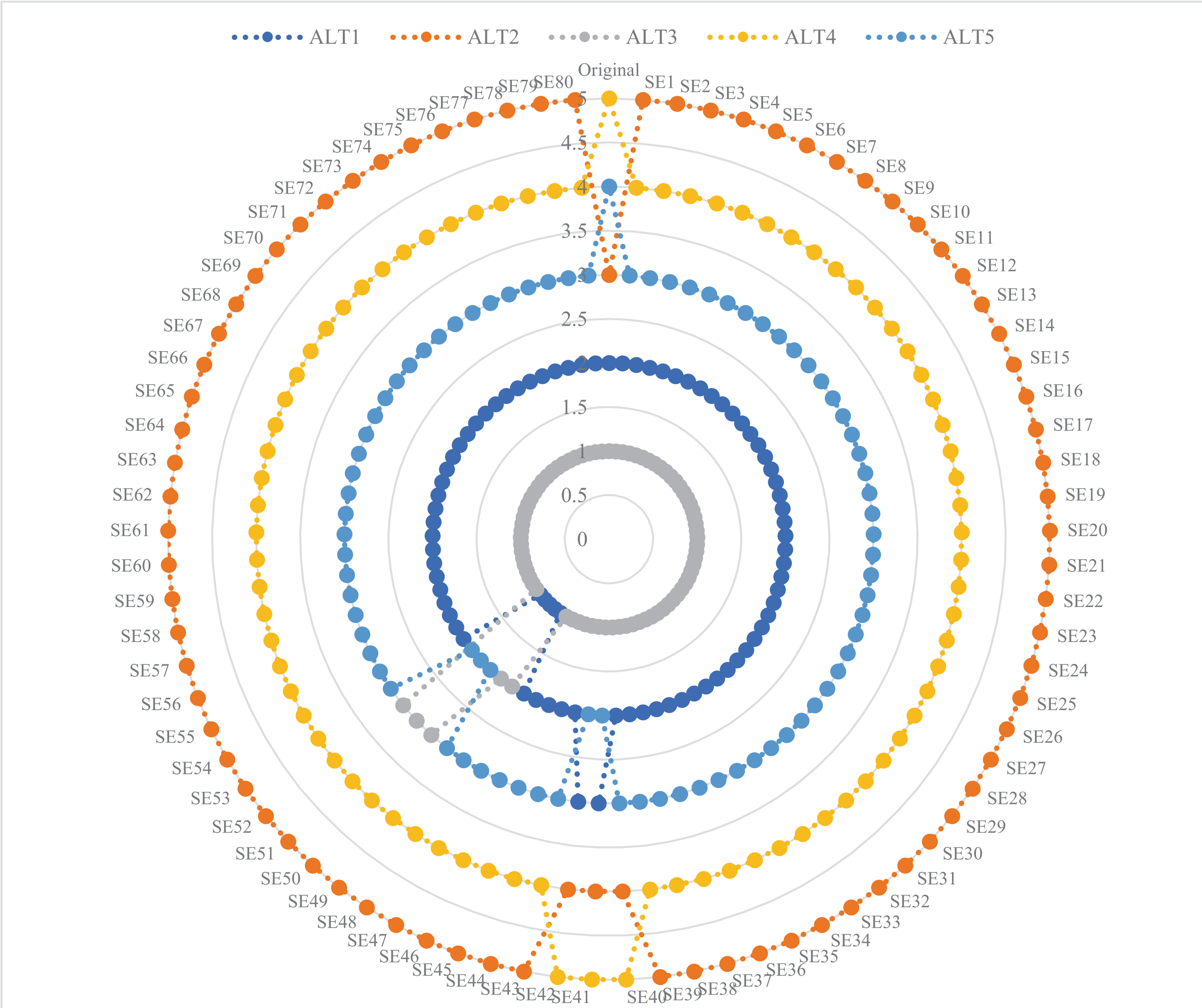


**Fig. 4.** Ranking change of alternatives of the weight change.

**Table 14**
Comparison of the rival methods.

| Rival Method | Ranking Principle | Rationale for Inclusion |
|---|---|---|
| TOPSIS | Calculates the geometric distance to both the Positive-Ideal Solution (PIS) and the Negative-Ideal Solution (NIS) | Included for its reliance on maximizing distance from the NIS, and minimizing distance from the PIS, a very common metric in MCDM |
| CODAS | Calculates the distance by Euclidean and Taxicab (or Manhattan) measures from NIS | Included because it depends solely on the distance to the anti-ideal, and it uses a unique combination of distance metrics for the assessment |
| MARCOS | Calculates the utility function based on the distance to both the Ideal Solution (IS) and the Anti-Ideal Solution (AIS) | Included because of its unique utility-based approach, which defines relationships relative to both the best and worst possible benchmarks |
| COPRAS | Calculates the proportional assessment by explicitly incorporating the sums of both favorable (benefit) and unfavorable (cost) attributes | Used as a benchmark in the comparison, since its proportional assessment method provides a clear and intelligible result for the DMs |

evaluated set, whereas ALT2 is identified as the least favorable option. It is noteworthy that a shift in the ranking of the best alternative occurs specifically in criterion five, which is the second most significant criterion in our model. This analysis demonstrates that the multi-criteria framework is responsive to alterations in criteria weights, highlighting that alternatives ALT3 and ALT1 emerge as dominant solutions.

**Table 15**
Comparative analysis results.

| Alternatives | PPF-WENSLO-COPRAS | PPF-WENSLO-TOPSIS | PPF-WENSLO-CODAS | PPF-WENSLO-MARCOS |
|---|---|---|---|---|
| ALT1 | 2 | 2 | 2 | 2 |
| ALT2 | 5 | 4 | 4 | 5 |
| ALT3 | 1 | 1 | 1 | 1 |
| ALT4 | 4 | 5 | 5 | 4 |
| ALT5 | 3 | 3 | 3 | 3 |

### 4.6.2. *Comparative analysis with alternative methods*

Here, the selection of rival techniques was made based on three criteria: (*i*) full compatibility with the proportional picture fuzzy domain, (*ii*) representation of different families of MCDM ranking mechanisms (distance-based, dominance-based, and utility-based), and (*iii*) widespread acceptance in recent fuzzy MCDM literature. Hence, PPF-TOPSIS (Zhao et al., 2025), Proportional Picture Fuzzy COmbinative Distance-based ASsessment (PPF-CODAS) and Proportional Picture Fuzzy Measurement Alternatives and Ranking according to COmpromise Solution (PPF-MARCOS) were chosen as benchmark methods,

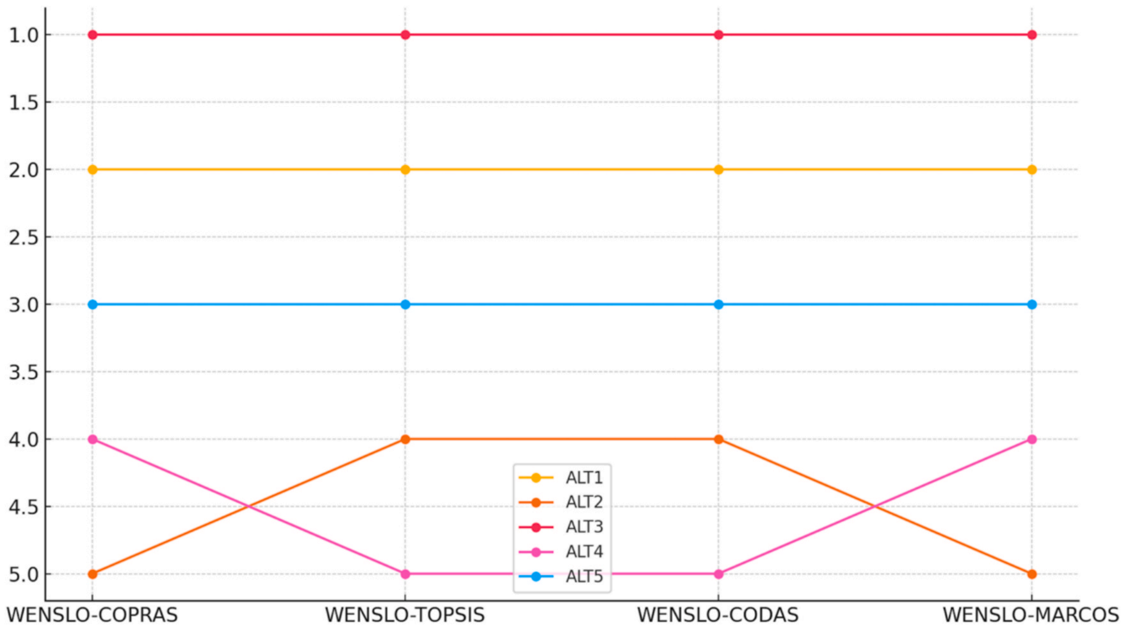


**Fig. 5.** Comparative analysis representation.

allowing us to assess whether the proposed AHC-PPF-WENSLO-COPRAS framework yields stable and method-independent rankings. The comparison methods are based on fundamentally different principles for deriving the final ranking, which makes them an effective benchmark for testing the stability of the proposed solution (see Table 14).

This comparison employs various MCDM techniques that utilize different data normalization approaches. All MCDM techniques are executed under consistent conditions. The comparative analysis results are outlined in Table 15, and Fig. 5 illustrates the results obtained from the three selected methods for comparison. ALT3 consistently emerges as a leading choice across all evaluated methods, while ALT1 maintains the second position, even as the methods vary. These differences suggest that, although ALT3 and ALT1 are recognized as strong alternatives, the exact ranking is influenced by how each method assesses the distance to both the ideal and anti-ideal references.

We are certain that the comparison confirms the consistency of the PPF-WENSLO weighting across different ranking logics:

- The rankings produced by PPF-WENSLO-COPRAS were compared with three other techniques; i.e., PPF-WENSLO-TOPSIS, PPF-WENSLO-CODAS, and PPF-WENSLO-MARCOS.
- All four ranking methods produced the same outcome: Corda (ALT3) consistently ranked first, while Hyperledger Fabric (ALT1) remained in second place.
- This stability, despite the methods relying on different normalization procedures and distance measures, including assessments relative to ideal and anti-ideal references, demonstrates the robustness of the PPF-WENSLO criteria weights and confirms the reliability of the overall ranking.

Our validation process followed two different stages to ensure the robustness and accuracy of the results: (1) sensitivity analysis of the criteria weights, and (2) comparative analysis with alternative MCDM methods.

## 5. Managerial Implication

This study conducted a holistic analysis using the MCDM approach to determine the most suitable blockchain technologies that can be utilized in the healthcare sector. The eight criteria utilized; i.e., integration, reliability, trust, efficiency, accessibility, cost, flexibility, and decentralization, are the key considerations that directly affect the technological solution preference of industry DMs. If the weight of the criteria is taken into consideration, the decentralization (0.219), accessibility (0.1721), and efficiency (0.149) criteria receive most of the importance. It shows that healthcare institutions put technical performance on their agenda, as well as ease of access and decentralized organization, when they assess digital solutions.

Study results show that Corda technology holds the highest performance level and ranks first. This success demonstrates the ability of Corda to balance decentralized design with easy user access and effective operation. Healthcare administrators gain a significant advantage from this in terms of secure sharing of patient data, intra-system collaboration, and regulatory compliance (Minango et al., 2025). Corda's process-driven design and facilitation of direct transactions between institutions give operational benefits, especially in fields of use such as supply chain management, tracking of patients, and data management.

The ranking of the study findings positions Hyperledger Fabric and Medicalchain technologies as second and third, respectively. As much as Hyperledger Fabric creates solutions specifically for institutional needs through its adjustable and modular setup, Medicalchain's patient-based design and strategy towards staying in control of health information by the users stand out (Androulaki et al., 2018). The finding suggests that managers of health should carefully evaluate unique blockchain solutions for each of the sub-areas. For example, if patient-oriented control of data is the priority, Medicalchain is the option, while Hyperledger Fabric might be ideal if integration is required in-house within processes (Wang and Qin, 2021).

Ethereum, although a widely used general-purpose platform, exhibits certain limitations in healthcare applications, including high transaction fees and limited flexibility. This highlights that healthcare managers must consider not only the popularity of a technology but also its contextual suitability. Technical constraints of Ethereum, such as energy consumption, transaction speed, and the scalability of smart contracts, can pose challenges in sensitive environments where patient safety and data management are critical (Kasyapa and Vanmathi, 2024).

Therefore, this study provides guidance not only for technological assessment but also for strategic alignment. Effective adoption of blockchain technology in the healthcare sector requires careful analysis of the criteria weights and evaluation of their alignment with organizational objectives. Healthcare managers must base digital transformation decisions not solely on technical capabilities but also on complex factors such as system compatibility, usability, and quality of service. In this regard, the proposed decision support approach facilitates more informed and strategic technology investments at the institutional level.

It is noted that the performance values in Table 13 have close margins within less than 0.001. Such clustering can be claimed for two reasons: (1) The alternatives represent the top-tier, mature blockchain technologies that are already advanced in healthcare, and therefore, their suitability is high across the board, and (2) the COPRAS normalization method scales the results against the best alternative, hence compressing the spread among highly competitive options. However, the practical significance of such small differences is verified by the sensitivity analysis (Fig. 4). Despite narrow numerical margins, the ranking order proves highly resistant to weight fluctuations. Consistent dominance of Corda (ALT3) within 80 variation scenarios and under different MCDM methods in Table 15 thus confirms that the ranking identifies a stable superior choice, determined by its decentralization and accessibility advantages rather than by random statistical noise. Finally, the following main implications are drawn:

I. **Practical Uniqueness of Corda:** The result that Corda is the best choice is important, as it indicates that solutions explicitly designed for specific application domains and sectoral needs (such as direct peer-to-peer data sharing, performance) are preferable by healthcare organizations over general-purpose, widely popular platforms like Ethereum.

II. **Criteria Prioritization:** Weights assigned using validation highlight, in order of importance, Decentralization, then Accessibility, and finally Efficiency. This spotlights the need for this sector for trust, low latency, and operational performance. This provides a practical, quantitative roadmap for managers to assess new technology investments.

III. **Model Innovation:** The integrated approach, featuring AHC for criterion simplification and PPFS for superior uncertainty modeling, offers a more transparent, adaptive, and resilient decision support model than fixed-weight or conventional fuzzy frameworks. This novelty is itself a critical practical contribution for MCDM applications in the high-stakes fields of healthcare.

## 6. Conclusions and Outlook

This study addressed the selection of blockchain platforms used in the healthcare sector. For this purpose, ML and MCDM methods were integrated, and the results were analyzed comprehensively. Since the number of criteria used in the subject and found in the literature is quite high and similar, the criteria were reduced and sorted, and the AHC method was used for this. Then, PPF-WENSLO was applied to determine the weights of the criteria, and PPF-COPRAS was applied to rank the blockchain technologies. Accordingly, a comprehensive sensitivity analysis was performed to analyze the accuracy of the method, and the method was proven to be accurate.

The results of this study clearly show that selecting blockchain technology in the healthcare sector requires a multi-dimensional examination. By employing the PPF-WENSLO-COPRAS methods in conjunction with PPFSs, this study objectively determines the weights of criteria and comprehensively ranks the alternatives. The analysis indicates that Corda technology emerges as the most appropriate option, as it demonstrates superior performance in key dimensions such as decentralization, accessibility, and efficiency. Although Hyperledger Fabric and Medicalchain also exhibit excellent performance, more general-purpose platforms like Ethereum and Algorand lag behind in terms of cost-effectiveness and flexibility (Minango et al., 2025). These results suggest that healthcare institutions should prioritize solutions designed for specific application domains and sectoral requirements rather than adopting widely popular platforms.

This research makes contributions to blockchain selection technology in healthcare by filling remarkable research gaps in the literature. No study has been identified that uses the PPF-WENSLO-COPRAS model together with PPFSs, and integration of ML and MCDM approaches is yet to be investigated in the scenario of blockchain selection in healthcare. This study has not only made the first application of these methodologies but also reformed them into a more meaningful framework by eliminating similar and duplicate criteria by using ML-based analyses. Therefore, a systematic decision support model was presented here for healthcare organizations to make their technology decisions more effectively, transparently, and logically, and an innovative contribution was also made to the literature on both methodological and applied levels.

At last, this work can be extended to some points; for example, involving more DMs and engaging a number of groups of stakeholders (hospital administrators, software developers, health authorities, etc.) in the evaluation process, which can provide more comprehensive outcomes. In addition to that, integration of data mining techniques such as AHCs with MCDM methods to cluster and then evaluate alternatives can generate more flexible analysis potentials in technology pools on a large scale. Furthermore, by incorporating additional variables such as environmental footprint, energy efficiency, and sustainability into the criteria set, advanced decision support models can be developed, particularly in the context of green healthcare technologies.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eswa.2026.131150.

## Data availability

Data will be made available on request.

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