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Prioritization of health distributed ledger technology use cases using fuzzy sine trigonometric based decision-making model

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A B S T R A C T

The transformative potential of Distributed Ledger Technology (DLT), particularly blockchain, is increasingly recognized in the healthcare sector for its ability to enhance security, transparency, and operational efficiency. This study introduces a novel decision-making framework, the fuzzy Sine Trigonometric COmplex PRo-portional ASsessment (fuzzy ST-COPRAS) model, to prioritize health DLT applications amidst the inherent complexity and uncertainty of healthcare data. The prioritization process is based on a comprehensive evaluation of multidisciplinary criteria, including economic viability, technological maturity, cybersecurity, and other critical factors. The ranking and prioritization of selected health DLT use cases-such as electronic health records (EHR) management, clinical trial oversight, pharmaceutical supply chain tracking, and telemedicine-are performed using the proposed algorithm, which incorporates tailored survey methods applied to experts in the field. The outcomes of this study are particularly valuable for standardization bodies, companies aiming to invest in DLT for healthcare, and governmental authorities seeking to allocate efficient support mechanisms and develop informed strategies. By identifying high-impact use cases, the findings provide actionable insights that facilitate strategic implementation, resource allocation, and policy development. Furthermore, the study highlights the alignment of blockchain-based solutions with regulatory requirements and techno-economic considerations, fostering trust and compliance. Overall, this research underscores the potential of DLT to revolutionize healthcare through secure, transparent, and efficient systems, driving significant advancements in patient care and system optimization.

1. Introduction

Distributed Ledger Technology (DLT), exemplified by blockchain, has emerged as a transformative force with the potential to revolutionize healthcare across multiple domains. This technology's decentralized and immutable nature offers enhanced security, transparency, and efficiency in managing sensitive health data and streamlining processes. While the potential applications of DLT in healthcare are vast, ranging from electronic health records and clinical trials to telemedicine and public health surveillance, prioritizing these diverse use cases is crucial for strategic implementation and resource allocation.

Although numerous studies explore DLT applications in healthcare, there is a lack of structured prioritization of these applications based on multidisciplinary criteria. Most existing research focuses on

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proposing technical frameworks without assessing their relative impact or strategic importance. This research addresses this gap by introducing a novel decision-making model, the fuzzy Sine Trigonometric COmplex PRo-portional ASsessment (fuzzy ST-COPRAS), to prioritize health DLT use cases. This new model uses fuzzy sine trigonometric functions in the fuzzy COmplex PRo-portional ASsessment (COPRAS) multi-criteria framework to make it possible to process uncertain information in a way that is not linear and is always changing. The fuzzy ST-COPRAS model's ability to handle complex and dynamic data sets it apart from traditional decision-making techniques, offering enhanced flexibility and accuracy in prioritizing health DLT use cases. Additionally, the fuzzy sine trigonometry logarithmic method of the additive weights model (fuzzy ST-LMAW) is applied to calculate the weights of the criteria. Fuzzy ST-LMAW represents developing the basic LMAW method (Pamucar et al., 2021) by applying non-linear functions of sine trigonometry.

This study explores the multifaceted applications of DLT in healthcare, examining the potential benefits and challenges in each domain. By applying the fuzzy ST-COPRAS model, we aim to prioritize these use cases based on a comprehensive set of criteria, including technological maturity, interoperability, scalability, cybersecurity, economic feasibility, and societal impact. This rigorous evaluation approach will provide valuable insights for healthcare stakeholders, policymakers, and investors, guiding them towards informed decisions that maximize the positive impact of DLT in healthcare.

There is an urgent need for transformative changes, such as those provided for Digital Health solutions as modern healthcare systems are under increasing pressure to deliver high-quality, patient-centered care while managing rising operational costs, staff shortages, and growing patient expectations, especially in times of economic uncertainty. The purpose of Digital Health is the integration of mobile technology and wearable devices in healthcare to improve the quality of life (QoL) of patients by providing advanced monitoring capabilities which ease the management of certain affections like diabetes (Rhee et al., 2020) or cardiovascular problems (Santo & Redfern, 2020). The main elements of digital health that benefit the management of disease like diabetes (Rhee et al., 2020) are continuous assessment of daily activities and eating habits with the help of wearables or smart phone applications dedicated to these tasks to measure the calorie consumption and intensity of the subject's physical activities, as well as advanced portable devices for blood glucose measurement that can store blood sugar data, analyze it with a smartphone, and inform the subject. For cardiovascular diseases (Santo & Redfern, 2020) the same monitoring strategy is applied ranging from text-based notifications for medication adherence to smartwatches that measure the heart rhythm and detect arrhythmias, help patients manage their disease in a consistent manner.

When assessing the impact of changes brought by Digital Health, one important notion to take into consideration is the digital literacy (Kemp et al., 2021) of the patients, as older patients may encounter different barriers in understanding the functionalities and how to utilize the application. This can be addressed by improving the development process of the application (Mathews et al., 2019) by following 4 standard steps technical validation, in which the performance, security and interoperability of the application is tested, followed by clinical validation the verify that it provides a defined clinical outcome. The last 2 steps consist in usability to assess the interactivity, ease of use of the application and the cost of the implementation which include set up training and solution management.

The implementation of Digital Health systems implies the need for secure data transfer, storage, and management due to the nature of the private information the smartphone or wearable devices send and work with. An alternative to centralized database systems is implementing distributed ledger technology (DLT) for security purposes (Bouras et al., 2020). DLT enables the implementation of decentralized (Antal et al., 2021) systems that support the registration, sharing, and synchronization of transactions. This allows storing the same data over multiple nodes while providing tamper proof protection based on the immutability of DLT technology. One of the DLT technologies is known as blockchain, that appends new transaction to the chain after it is encrypted and confirmed, after which the blocks are timestamped and cryptographically linked to previous blocks.

In the case of blockchain, immutability is assured by the auto-generated header of each block combined and hash key that contains the header of the previous block, the transactions cannot be altered unless over half of the of the nodes agree to the modifications (Lashkari & Musilek, 2021) DLT implementation can be based on Directed acyclic Graph (DAG) or Hybrid DLT. In DAG technology each transaction acts as a node and requires the authentication of prior transactions to join the graph. Hybrid DLT combines the previous blockchain technology with DAG which can result in a hybrid DLT with improved security and speed that can satisfy the needs of scalability (Farahani et al., 2021).

The potential impact of DLT in healthcare has attracted significant attention in research due to its potential to address industry complexities involving diverse stakeholders, systems, and regulations. A structured review of 185 studies done in Beyene et al. (2022) identified six key use cases for DLT in healthcare, each serving distinct purposes and requiring specific technical and administrative features. The study highlights the varying requirements of these use cases, emphasizing the importance of customized DLT implementations. By identifying these needs, the paper aims to guide practitioners in developing practical applications and encourage further exploration of less-studied areas within healthcare's DLT landscape. Carlos Ferreira et al. (2024) reviewed existing research on distributed ledger technology (DLT) in genomics using a scoping review and thematic analysis. Seven key themes are identified: data economy, sharing, management, protection, storage, proof of useful work, and ethical, legal, and social issues. Authors show that although research in this area expands, many questions remain unresolved. Future research directions were proposed to support the adoption of DLT in genomics. Hu et al. (2024) address challenges in managing and exchanging electronic health records (EHRs) due to fragmented systems, varied standards, and security issues. It proposes using distributed ledger technology (DLT), like blockchain, to enhance healthcare security, transparency, and data sharing. The study outlines an implementation strategy focusing on encryption, access control, and necessary standards for interoperability.

In this study, a mathematical framework for decision-making based on the application of non-linear fuzzy functions of sine trigonometry is presented. Fuzzy functions of sine trigonometry were used because they successfully treat and exploit uncertainties in information. Sine trigonometry functions are implemented in the fuzzy COPRAS multi-criteria framework to improve the adaptability of the traditional COPRAS model. It is one of the Multi-Criteria Decision Making (MCDM) techniques. The MCDM techniques have been successfully integrated into many various of decision making problems in the literature (Ali et al., 2025; Basirat et al., 2025; Kara et al., 2025; Seifi et al., 2025; Wang et al., 2025; Yardım et al., 2025).

In addition to the above, the proposed multi-criteria methodology has the following advantages: i) Within the fuzzy sine trigonometric COPRAS (fuzzy ST-COPRAS) model, fuzzy functions are implemented that enable non-linear and adaptive processing of information within the home matrix; ii) The proposed fuzzy ST-COPRAS methodology enables rational reasoning and objective presentation of information around the origin; iii) Application of non-linear fuzzy functions enables non-linear processing of complex and uncertain information that cannot be processed using traditional linear functions that are characteristic of the traditional COPRAS method; iv) Fuzzy ST-COPRAS has adaptability and the ability to generate different scenarios within the sensitivity analysis. This feature of the proposed methodology allows us to see the implications of dynamic and uncertain information on the final results.

Considering the presented characteristics of the fuzzy ST-COPRAS technique, we can conclude that the presented technique has a greater degree of generality and flexibility than traditional MCDM techniques.

This paper makes several significant and impactful contributions to the field of healthcare technology and decision-making models:

1) Introduction of a novel decision-making framework: It presents the fuzzy Sine Trigonometric COPRAS (fuzzy ST-COPRAS) model, an innovative decision-making methodology specifically designed to prioritize health DLT use cases. This framework leverages fuzzy sine trigonometric functions to effectively address the inherent complexity, uncertainty, and non-linear dynamics of healthcare data.
2) Comprehensive evaluation of health DLT applications: The study evaluates and ranks nine critical health DLT use cases, including electronic health records (EHR) management, clinical trial oversight, pharmaceutical supply chain management, telemedicine, and public health surveillance. These use cases are assessed against multidisciplinary criteria, providing a holistic understanding of their potential impacts on healthcare.
3) By presenting a robust prioritization framework, this research equips healthcare stakeholders-such as policymakers, public and private healthcare providers, standardization bodies, and investors-with actionable insights to inform strategic resource allocation and implementation. The resulting rankings act as a practical tool for identifying high-impact use cases and guiding optimized investment decisions.

Overall, this research bridges gaps in decision-making within healthcare technology by offering a methodical, data-driven approach to evaluate and implement DLT use cases, driving advancements in secure, efficient, and transparent healthcare systems.

The structure of the paper is as follows: Section 2 introduces the primary use cases of distributed ledger technology (DLT) in healthcare. Section 3 outlines the criteria used for ranking these use cases. Section 4 presents the proposed research model for decision-making. Sections 5 and 6 detail the application of the model and provide a discussion of the results. Section 7 highlights the study's implications for policymakers, and the paper concludes with a summary of findings.

2. Health DLT use cases

The nine health use cases where DLT can be used are investigated in this study (see Table 1). The selected use cases are shortlisted based on the expert opinion of coauthors and literature research.

2.1. Electronic health records (EHR) management

EHR is a fundamental part of clinical informatics, which contains a longitudinal (past, current, and future) view of all patient interactions with the healthcare system. We can consider that EHRs have reached their third generation, starting from paper-based records to digital documents, then adding support for complex workflows, and now supporting clinical decisions, public health, continuity of care, or interoperability. Due to their properties and requirements, EHR can greatly benefit from the introduction of DLT; in fact, a report shows that most healthcare industry experts predict that EHR, along with clinical trials and supervised compliance, can benefit from DLT (IBM, 2023).

Table 1
DLT in health use cases.

Use case number	Use case name
A1	Electronic health records (EHR) management
A2	Clinical trial management and Research
A3	Pharmaceutical supply chain management
A4	Medical device tracking and IoMTs
A5	Telemedicine
A6	Public health surveillance
A7	Health insurance and Payment Settlement
A8	Interconnected Smart Health
A9	Governance Aspects: Policy, Legal, legislative elements and Cyber Ethics

Let us review some of the properties of EHR that make them prime targets for the introduction of DLT. First, the EHR should be patient-centric, making the patient the sole owner of her/his medical data, allowing him to choose to whom those data are shared and for how long. This can be achieved using DLT and smart contracts, for example, in Chen et al. (2019) the authors propose a DLT-based medical data storage, in which the medical data are encrypted and stored off-chain, and patients can authorize access to parts of the medical file. The same is shown in Mandarino et al. (2024) in which, in addition to security, cost-efficiency is also targeted, by storing data off-chain.

Similarly, in Azaria et al. (2016), Medrec is introduced, focusing on EMR authentication, confidentiality, and data sharing using Ethereum smart contracts. Medchain (Shen et al., 2019) makes the access control more finely-grained, supporting sessions. Another property of EHR is the focus on longitudinal data; an EHR should access medical data from multiple encounters with different healthcare providers, data that should not be siloed. An example of supporting this feature through DLT is presented in Fan et al. (2018), in which data are stored where they were produced and DLT holds only summary and digests and allows access based on smart contracts to the original data. This also highlights other properties of EHR, immutability and verifiability of medical data, which is achieved by storing digests on the chain. EHRs should also be the basis of clinical decision support, where DLT can be used to provide clinicians with real-time access to relevant data and evidence-based guidelines, helping to improve the quality of care (Mayer et al., 2020).

2.2. Clinical trial management and research

Some key issues found in clinical trial management are data integrity, data sharing, data privacy, patient enrollment, and research reproducibility. DLT can be used in all phases of clinical trials, including the collection and analysis of data. DLT can be used to facilitate the coordination and management of clinical research studies, including the recruitment of participants and the collection and analysis of data. For example, in Benchoufi and Ravaud (2017) authors present how data integrity and traceability in a complex clinical trial data workflow can be supported by DLT, by storing on chain and time stamping, to ensure the chronological order, the relevant data or metadata such as data-sharing plan, consent and clinical trial protocol, statistical analysis plan and analytical code.

Multi-site clinical trials are approached in Choudhury et al. (2019) in which a Hyperledger-based DLT is compared to a traditional, centralized system for data management, obtaining better results in terms of data privacy (using private channels), data storage and recovery (decentralized and redundant). Both studies propose the use of smart contracts for facilitating clinical trial enrollment, for example by checking prerequisites such as age, health condition without making the data public. DLT can be used to track the progress of drug development, including the collection and analysis of data from preclinical and clinical trials. A feature of DLT is supporting transactions or workflows between trustless entities. This can be used in collaborative drug discovery (Olsson & Toorani, 2021) in which DLT can be used to share only part of the information on new drugs, keeping critical information confidential. Another important feature in clinical trials is stakeholder interoperability, addressed in Nnadiekwe et al. (2024), which promotes a patient-centric approach by allowing patients to use smart contracts to report any adverse effects.

2.3. Pharmaceutical supply chain management

Current distribution method of pharmaceutical products has an innate flaw that make the supply chain vulnerable to appearance of substandard or falsified products. This flaw is created by the increased complexity of the supply chain, lack of transparency, outsourcing the production process globally and importing ingredients from multiple countries different from the drug distribution locations. These allow for unethical actions to happen and influence the drug quality (Ahmadi et al., 2020; Lingayat et al., 2021).

To prevent the issues that arise from lack of recorded or falsified information due to lack of transparency, a digital ledger system based on blockchain would help as there are multiple strong points that support the use of blockchain in pharmaceutical supply chain distribution (Erokhin et al., 2020), such as decentralized management which permits collaboration between healthcare partners without a central management intermediary, immutable audit trail as it only allows the create and read data, data provenance as the data can only be changed by the owner, robustness, availability and the most critical security and privacy using cryptographic algorithms (Kuo et al., 2017; Lingayat et al., 2021). The blockchain technology can be used due to the above reasons for improved health record management, insurance claims and health care ledgers.

A concrete example would be the implementation of Hyperledger Fabric (open source blockchain technology) combined with smart contract for drug supply chain management in a hospital. The proposed system (Jamil et al., 2019) would create a drug record transaction and then launch a smart contract to give temporary time access to drug and patient electronic records. The blockchain based system was tested for performance issues and experiments indicate an improvement of throughput and minimized latency with minimum resource utilization compared to other blockchain systems, the tests were done with Hyperledger Caliper a benchmarking tool for blockchain technology. The authors specify that a real environment test is required to observe the feasibility of the implementation.

Another example of an implementation (Jangir et al., 2019) scenario is based on the use of Ethereum blockchain, a DLT technology that supports self-running smart contracts that would help resolve the previously mentioned problems posed by normal centralized supply chain methods. The proposed model involves drug suppliers, manufacturers, raw materials contracts, distributors, and stock purchase contracts until the retailers and medicine purchase maps. Each step verifies for the quality and ownership and all the transactions are stored on DLT. The performance related results indicate that an improvement in the framework is required as there is a scalability issue and transaction speed may decrease in a large-scale operation.

Also, for supply chain management, a synergy of technologies such as blockchain and IOT is presented in Mangala et al. (2024), in which IOT devices are used for keeping track of the state of medical items while blockchain offers time-stamping and immutability for tracking.

There is a need to specify that there are some challenges (Etemadi et al., 2021; Kuo et al., 2017) that prevent the adoption of blockchain technology and that are required to be addressed, such as transparency over confidentiality, the decrease in speed scalability, and malicious node attacks that could happen when the infected nodes in a network surpass the number of real nodes.

2.4. Medical device tracking and IoMTs

In today's era, the Internet of Things (IoT) devices are in great demand in many aspects of lifestyle and living. The Internet of Things is a group of devices and services with decentralized management.

The IoMT (Internet of Medical Things) is a suite of software applications and medical devices and sensors connected to healthcare centralized or distributed IT systems using the Internet or any computer network, mainly WiFi, to better provide healthcare services to the patient (e.g. remote patient monitoring). Taking in consideration the decentralized nature of Blockchain / Distributed Ledger Technologies, the IoT and IoMT are effortlessly interconnected using these technologies to build an integrated system.

As a use case for diabetes patients management, BlockMedCare (Azbeg et al., 2022) presents an integration of IoT and IoMT with Blockchain (Ethereum based) to create an integrated secure healthcare system. Another use case for COVID-19 patients management presents an IoMT integration with Hyperledger fabric (Almalki et al., 2022) focusing on security of the entire framework.

The major example of a blockchain-based integrated system to track medical services and supplies from the manufacturing point to the very final end user is MediLedger, a data validation and settlement application (Mattke et al., 2019). The major benefit of such ecosystem is the supply chain optimization and compliance through transparency (enabling the whole supply chain data aggregation for medical services and supplies providers). FarmaTrust is one successful implementation for blockchain-based "pharmaceutical tracking and data services"; services are provided in London, UK (Rojnic, 2022). Preventive maintenance is a critical aspect in medical devices, and in Omar et al. (2024), authors describe how blockchain can be used for increasing accountability in the maintenance of medical imaging equipment, reducing the risk of equipment failure.

2.5. Telemedicine

Telemedicine is one of the healthcare areas with the fastest growth in the COVID-19 pandemic. This growth, however, was built on top of legacy, centralized systems, unable to fulfill critical requirements such as security and privacy or operational transparency (Ahmad et al., 2021). DLT can be used to facilitate the delivery of next generation, decentralized remote healthcare services, including the secure exchange of medical data and the scheduling of appointment. DLT can enable the services to be tamper-proof, traceable and reliable. Key areas for DLT in telemedicine are the traceability of remote treatment, of monitoring devices, securing access to electronic or personal health records, automated payments, trustworthy insurance services and reputation aware, public and transparent specialist referral services.

One example of a DLT-enabled telemedicine service is presented in Mannaro et al. (2018), more specific, a teledermatology project, DermoNet. Authors propose a virtual organization in which the actors in the system use smart contracts to communicate, patients being able to securely connect to dermatologists, without using the GP as an intermediary, and to upload their encrypted medical data (pictures) that only the assigned doctor can view. Doctors are also rated and the platform also supports clinical trials. A key feature is that the patient is always in control of her/his medical data. Combining AI and blockchain, Harshithan and Kurian (2024) highlights the role of blockchain in authentication and secure management of e-prescriptions generated as an outcome of a telemedicine session.

2.6. Public health surveillance

There are many challenges in the proper management of an epidemic, ranging from medical data sharing, breaches of privacy or lack of real-time data gathering tools. DLT represents a new way of improving current health care systems used for infection disease monitoring and outbreaks. This decentralized model assures the confidentiality, availability, and integrity of data without the involvement of a third party that can be exposed to security risks. The needs for such a system increased in the last years due to the recent pandemic. Multiple models have been proposed to manage outbreaks and reduce the stress on healthcare infrastructure, one of the models iBlock (Egala et al., 2021) uses the blockchain technology to collect user data and validate it before publishing it to a repository and running background processes that analyze the data using Artificial Intelligence and Machine Learning operations to predict survival rate, labeling high risk areas that help in the pandemic management and mitigation process.

Similarly (Khan et al., 2024) proposes the use of machine learning and blockchain for tracking infectious disease, the model using blockchain oracles for tracking events about COVID-19, extract meaningful features for training the epidemic model. In addition smart contracts are used for quering the deployed model.

Another model (Zhu et al., 2021) proposes the use of PBFT(Practical Byzantine Fault Tolerance) consensus algorithm for an infectious disease tracing method that improves its efficiency compared to the PoX(proof-of-transfer) mechanism. DLT based systems (Hasan et al., 2021) can help with epidemic tracking and monitoring as they have a non-tamper able and traceable architecture that assures data credibility. It helps identify credible suppliers for medical equipment with a transparent and auditable product transaction and most importantly it offers authentic information due to its decentralized consensus mechanism (Nguyen et al., 2021). A consistent issue in this type of model is the latency present in distributed networks compared to centralized structures that can affect the scale of the deployment, an improvement might be made with a newer proof-of stake model that has a better performance (Shae & Tsai, 2017). Some of the challenges of blockchain technology are related to data authenticity that needs to be verified before being uploaded on the blockchain, data actualization that need to update older data to newer information, and storage as the data stored on blockchain required high capacity storage resources (Zhu et al., 2021).

2.7. Health insurance and payment settlement

Using DLT (Distributed Ledger Technology) position itself as a major technology appropriate to store, exchange and share data, the whole insurance claim process can be improved. The chain used in the claim process is standardized in Fast Healthcare Interoperability Resources by HL7 organization (FHIR, 2023). In Table 2 is presented how each above mentioned benefit will translate into a real life activity improvement.

The traditional approach for healthcare insurance has tree steps: claims, verification, reimbursement. Usually the health care provider offer patient's services and then submits a claim. This claim is verified and paid by the same entity, the insurance company or the health organization. Since the patient is left out of this chain, major health care fraud and abuse could happen. Blockchain / DLT (Distributed Ledger Technology) enables the required transparency and secure data management that mitigates this risk that could be in the billions order of magnitude per fiscal year (Justice Dept, 2023).

A useful research is the framework proposed by the University of California School of Medicine, San Diego Supercomputer Center, AEEC Innovation Lab (Mackey et al., 2020) and funded by the San Diego Supercomputer Center BlockLAB. The technical framework was focusing on the US Medicare claims process using the blockchain Ethereum Foundation platform (Ethereum Foundation, 2023) and having as central authority the US Centers for Medicare and Medicaid Services (CMS).

We should mention prominent integrated systems, such the one operated by HealthVerity (Verity, 2025), where multiple healthcare providers can keep track of payments for any services. Also, a model for health insurance claim system is presented in Alamsyah and Setiawan (2025), particularized for Indonesia, noting challenges such as interoperability, regulatory compliance, cost and user readiness.

Table 2
DLT in health insurance and payment settlement.

DLT benefit	Activities improvement
Data availability	Easy access for patients.
Auditing without modification	The fraud detection is improved and discovered during audit.
Data traceability	The source of each record can be verified.
Privacy and increased security	Increased security, no identity theft, secure payments.
Distributed management	The insurance claim process is real time.

Presented as another use case, one of the best real life example is the health records management in Estonia by the company Guardtime, a cybersecurity systems provider (Guardtime, 2023; Platform, 2023). Using Blockchain and DLT (Distributed Ledger Technology) based systems in Estonia they securely manage over 1 million patients' health records and more than 300 million health events (eHealth, 2023).

2.8. Interconnected smart health

Smart Health is a new domain that combines Internet of things (IoT) technology with health monitorization systems to obtain an improved way of delivering health services to the patient in a smart city. Smart cities are based on sensors that provide diverse information regarding their location as humidity, temperature, traffic conditions and others. Smart Health combines the infrastructure of smart cities with mobile health to provide the patient with information's obtained from the smart city regarding the environment (Al-Azzam & Alazzam, 2019), such as pollution levels, pollen concentration in the air, and combine them with the patient profile to offer, for example, advice on what to do for preventing possible health risk in case of allergies and show the shortest route to the nearest pharmacy that have the required drugs. In essence it is intended to promote interactions between all healthcare agents by using intelligent monitoring devices and aid the in the decision-making process and resource allocation (Sundaravadivel et al., 2017; Tian et al., 2019).

Smart Health systems can be improved with the use of blockchain technology that offers an immutable database that stores information in a chronological order as well as cryptographic algorithms applied to the stored data which improves the security by allowing access only to authorized personnel (Agbo et al., 2019). These traits of blockchain combined with data generated from the IoT devices creates reliable data that cannot be tampered which can further be used to deduct further patterns and models for improving the current Smart Health system. The benefits offered by Smart Health systems can be minimized by the potential threats, information security (Karunarathne et al., 2021) for the patient, provider and developer and as medical data represents an sensitive issue (Sundaravadivel et al., 2017).

As it is an network based system, the security is affected by cyber attacks such as denial of service(DoS) that would affect the reliability and availability of the system, Fingerprint and Time Based Snooping(FATS) or Select Forwarding (SF) attacks that affect data reliability and compromise its integrity (Butt et al., 2019). IoT devices are more vulnerable to these attacks as they are lightweight (Tariq et al., 2020) by design and cannot include a strong security service that consume its power supply in the background.

As iterated above data quality and security can be obtained with the use of different blockchain models, a proposed (Chakraborty et al., 2019) model suggests the use of two blockchain networks for improving the transaction and access management to maintain a high level of security, one network Personal Health Care (PHC) Blockchain that is maintained by the patient from which data from sensors are taken and send to the doctor for analysis. The second External Record Management Blockchain is used for managing the data that is created when a patient visits the doctor and uses the "Proof of Stake" algorithm to append the data to the blockchain. For the IoT devices a lightweight cryptography primitives algorithms can be implemented to collect and store data securely. Therefore, Smart Health system should take consideration the integration of distributed ledger technology in their design for data quality, acceptability and security.

Another area in which DLT solutions can enhance the impact of smart health is in securing data used in machine learning models. By using federated learning, as is described in Khan et al. (2025), more stakeholders to participate in model training without exposing raw data. As such the implementation of smart health system based on DLT can provide a wide range of opportunities for new services and health applications. These opportunities consist in:

- Data collection and ownership for due to the decentralized nature of DLT (Golosova & Romanovs, 2018) eliminating the need of a central administrator or third party owner as this kind of system allows the collection from multiple city sensors with users health information.
- Prevention and management of severe incidents with real time reliable, transparent data assured by DLT immutability and transactions copying process, offered to the authorities for fastest route in case of an accident.

2.9. Elderly care

Most ambient assisted living (AAL) solutions, including smart homes, combined with IoT, telemedicine, domotics, smart wearables and other remote monitoring technologies, target elderly care or the care of chronically ill including those with neurodegenerative disease. Thus, many issues with the application of DLT for elderly care are the same as for telemedicine and medical device tracking. One key area in which DLT can be an enabler for AAL solutions is trust management (Velmovitsky et al., 2020), by managing the process of informed consent, ensuring transparency of medical data collection. Data decentralization inherent in DLT enables data ownership and can also raise trust in AAL (Calvillo-Arbizu et al., 2021). Similarly with EHR, DLT can be used in AAL to manage data access for formal or informal carers.

Another use case is implementing smart contracts that execute automatically based on monitored data, for example in smart homes, calling emergency services when life-threatening situations are sensed, Tantidham and Aung (2019) using a secure system that is more resistant to cyber-attacks. One of the most frequent use case in elderly care smart solutions is fall detection. In Rupasinghe et al. (2019) authors present a DLT-enabled system for fall prediction, in which the blockchain is used for aggregating fall-relevant information from multiple sources, ensuring data provenance, data availability, security and privacy.

One systematic review (Tlemçani et al., 2025), focused specifically on the use of blockchain and edge computing in diabetes management has highlighted that security, privacy, real-time processing, efficiency and scalability are the health challenges targeted by the introduction of these technologies. We can conclude that DLT enhances elderly care by enabling secure, transparent, and decentralized data management, enabling trust and automation in AAL and chronic care solutions.

3. Criteria

3.1. C1-technological maturity

The concept of technological maturity is an essential aspect of research and development (R&D), planning for developing technologies, and the process of making decisions on technology investments. A specific technology's location on the evolutionary curve may be determined by its technological maturity level, which also indicates how near the technology is to being implemented in applications that are utilized in the real world.

3.2. C2-interoperability

In blockchain for health applications interoperability refers to the interconnection and interaction of various cyber-physical components within a multidimensional and multi-layer ecosystem, which satisfies the safe and robust operation of the proposed system and subsystems.

3.3. C3-scalability

When discussing use cases for blockchain technology in the health care industry, the scalability elements pertain to several dimensions, such as a cap on the total number of stakeholders who may actively engage in the blockchain network. As a result, one way to evaluate scalability is to determine the order of magnitude of simultaneous participants who can conduct error-free transactions on the blockchain.

3.4. C4-transaction speed

In the context of the health blockchain use case, the term “transaction speed” refers to the rate at which transactions may be carried out in relation to the total number of transactions. When opposed to an hourly market or a 15-min market, for example, the impact of transaction speed is far less significant in a day-ahead market. Therefore, every blockchain solution has to be assessed in terms of the maximum number of simultaneous transactions it can support at any one moment without overwhelming the network.

3.5. C5-cybersecurity and digital privacy

Cybersecurity elements study hazards connected with interactions between blockchain DLT and the health use cases. The management of keys, scalability, authorization methods, and the implications that they have are some of the cryptographic selection and performance features that are addressed in this article. DLT can be used to facilitate the sharing of healthcare data between different parties, such as hospitals, laboratories, and researchers, while still maintaining the privacy and security of the data.

3.6. C6: Economic feasibility

(OPEX and CAPEX): It is vital to assess the economic viability of a digitalization investment project that employs some kind of DLT, just like it is essential to check the economic viability of any other investment. Capital Expenditures (CAPEX), which may be incurred by such expenditures, may include the administration of projects, the design of systems, and the creation of both hardware and software components. In the meanwhile, the Operational Expenditures, also known as OPEX, are the cost components that are linked with the operation and maintenance of the existing system. These costs may also include the transaction fees. Economic Value Creation: This criterion is related to the degree of value created by using DLT for a specific use case by eliminating the third parties, accelerating the processes, increasing the efficiencies, reducing the costs, and/or increasing the benefits.

3.7. C7-energy and resources consumption

The energy consumption of blockchain technology has become a major concern, especially since diverse applications are being examined. The consensus procedures used in a permissionless DLT architecture, such as proof-of-work, need substantial computing power and energy usage, which might result in a considerable carbon footprint.

Permissioned DLT systems, such as Hyperledger Fabric, provide consensus mechanisms that are less energy-intensive. This may greatly lower the blockchain system's energy usage. While evaluating the usage of blockchain technology in healthcare, it is crucial to examine the effect of such applications on the overall amount of energy consumed. This research should consider not just the energy consumption of the blockchain system itself, but also the infrastructure linked with it, such as servers and data centers. It is also important to note that the energy consumption of blockchain technology is a social and political problem as well as a technological one. It is vital to evaluate the tradeoffs between the advantages of blockchain technology and its influence on the environment and energy consumption. Despite the fact that blockchain technology provides numerous potential advantages to the healthcare business, it is essential to examine the energy and resource consumption connected with its usage and to identify ways to limit its environmental effect. In addition to electricity consumption, Blockchain-related operations may also need other hardware and resources.

To keep the ledger data, which may increase rapidly as more transactions are added to the network, blockchain networks need storage. This necessitates the installation of storage space, which may be costly and needs upkeep. Nevertheless, blockchain networks may need strong CPUs, GPUs, graphics cards and other hardware for mining and other computational heavy operations. In addition to being expensive, these components may need periodic updates to ensure maximum performance.

Bandwidth for data transmission, cooling systems to avoid overheating, and backup power sources to prevent data loss in the case of a power outage may also be necessary for blockchain projects.

Furthermore, blockchain technology may have indirect impacts on other resources, such as the amount of water required to cool data centers and the amount of rare earth metals necessary to manufacture hardware. In analyzing the environmental effect of blockchain technology-related initiatives, it is crucial to examine not just energy consumption but also the usage of other resources. Using more energy-efficient hardware and maximizing resource utilization are two strategies that may assist lessen the environmental effect of blockchain technology.

A recent performance evaluation comparing blockchain and IOTA-based DLTs in e-healthcare settings indicated that Ethereum consumes approximately 40,000 kWh per million transactions, while Bitcoin consumes over 818,000 kWh per million, in comparison to IOTA's 0.00188 kWh per million at 50 transactions per second (TPS) and 0.00068 kWh at 200 TPS, making IOTA over 10 million times more efficient in terms of energy consumption than Bitcoin for high-volume healthcare data exchanges (Minhas et al., 2023). Furthermore, a comparative study of Ethereum, Hyperledger Fabric, and Tencent Chain in healthcare applications showed that Hyperledger Fabric consumed the least energy at 0.95 kWh per 1000 transactions, followed by Tencent Chain at 1.25 kWh, while Ethereum consumed 2.75 kWh per 1000 transactions, making Fabric 2.89× more energy-efficient than Ethereum for processing health-related smart contracts (Minhas et al., 2023). Depending on the healthcare use case, its architecture size, and the selected DLT method, the performance indicators in terms of resource consumption values vary.

3.8. C8-contribution to United Nations sustainable development goals and other societal impacts

The use cases are assessed in relation to the 17 Sustainable Development Goals (SDGs). For instance, the implementation of blockchain technology in the healthcare industry could result in the development of innovative new technologies for use in the industry (Goal 9), which would lead to affordable and environmentally friendly energy (Goal 7), and pave the way for the creation of sustainable communities and cities (Goal 11). The bigger the number of Goals that are addressed, the better the rating of the use case.

3.9. C9-governance aspects: Policy, legal, legislative elements and cyber ethics

Policy, Legal, legislative elements and Cyber Ethics: are governing the rules of the game, which brings us to the topic of legal and legislative interoperability. Any formal market in a country has to be regulated, and that duty falls on the nation's policymakers. For the purpose of declaring the particular sets of regulations, legal documents and laws are used. It is necessary that the various legal and legislative systems effectively interoperate with each other and with the many areas, which each have their own unique sets of legitimate legislative papers. The backing of policymakers and the variables that drive them, such as public acceptability and cyber ethics, have the capacity to influence the choice to undertake an investment.

3.10. C10-industrial standardization

Industrial standards are in general used for harmonisation of different solutions and interoperability. They ensure that solutions from different providers can work well together. As in medical informatics many different players (medical units, pharmacies, insurances, governmental bodies, etc.) are present, it is important to use standards for interoperability and harmonisations of different solutions from different providers

The set of ten evaluation criteria used in this study was derived through a structured expert elicitation process involving senior members of relevant IEEE Standards Association working groups focused on blockchain and DLT standardization. Their insights were combined with a targeted literature review to ensure that the criteria reflect both current academic perspectives and evolving industry practices. While comprehensive, this set does not claim completeness or exclusivity; future research may expand or refine these dimensions based on emerging technological, regulatory, or clinical considerations. Notably, we distinguish between interoperability (C2)-which addresses the technical capacity of systems to exchange and use data-and industrial standardization (C10)-which concerns adherence to formal norms, frameworks, and compliance standards. This distinction is important to preserve granularity in evaluating DLT readiness in diverse healthcare contexts.

4. Proposed research model

This section gives the basic operators under fuzzy sine trigonometric norms and their definitions. Additionally, the steps of decision making model are provided to handle the weights of the criteria, and to rank the alternatives.

4.0.1. Trigonometric t-norm and t-conorm

Definition 1. Assume that ϑ_1 and ϑ_2 meet the condition that $(\vartheta_1, \vartheta_2) \in [0,1]$, then we can define the trigonometric T-norm and T-conorm between ϑ_1 and ϑ_2 as follows (Hu et al., 2015):

$$\Theta_T(\vartheta_1, \vartheta_2) = \frac{2}{\pi} arcsin\left(sin(\pi\vartheta_1/2) sin(\pi\vartheta_2/2)\right) \tag{1}$$

$$\Theta_T^c(\vartheta_1, \vartheta_2) = \frac{2}{\pi} arccos\left(cos(\pi\vartheta_1/2) cos(\pi\vartheta_2/2)\right) \tag{2}$$

where $(\vartheta_1, \vartheta_2) \in [0,1]$.

Then, based on the definition of trigonometric T-norm and T-conorm, we can define some trigonometric operational lows of fuzzy numbers $\tilde{\gamma}_1 = (\gamma_1^l, \gamma_1^m, \psi_1^u)$ and $\tilde{\gamma}_2 = (\gamma_2^l, \gamma_2^m, \gamma_2^u)$.

Definition 2. Let's assume that $\tilde{\gamma}_1 = (\gamma_1^l, \gamma_1^m, \gamma_1^u)$ and $\tilde{\gamma}_2 = (\gamma_2^l, \gamma_2^m, \gamma_2^u)$ represent fuzzy numbers, where γ_1^l and γ_2^l represent lower limit, γ_1^u and γ_2^u represent upper limit, while γ_1^m and γ_2^m represent modal values of fuzzy numbers. Also, suppose that $\upsilon > 0$, $f(\tilde{\gamma}_1) = \tilde{\gamma}_1 / (\tilde{\gamma}_1 + \tilde{\gamma}_2)$ and $f(\tilde{\gamma}_2) = \tilde{\gamma}_2 / (\tilde{\gamma}_1 + \tilde{\gamma}_2)$, then we can define the following operations:

1) Addition "+"

$$\tilde{\gamma}_1 + \tilde{\gamma}_2 = \left(\left(\tilde{\gamma}_1 + \tilde{\gamma}_2 \right) \frac{2}{\pi} arccos\left(cos\left(\pi f(\tilde{\gamma}_1)/2\right) cos\left(\pi f(\tilde{\gamma}_2)/2\right) \right) \right) \tag{3}$$

2) Multiplication "×"

$$\tilde{\gamma}_1 + \tilde{\gamma}_2 = \left(\left(\tilde{\gamma}_1 + \tilde{\gamma}_2 \right) \frac{2}{\pi} arcsin\left(sin\left(\pi f(\tilde{\gamma}_1)/2\right) sin\left(\pi f(\tilde{\gamma}_2)/2\right) \right) \right) \tag{4}$$

3) Scalar multiplication $\Omega \in (0, +\infty)$

$$\Omega \times \tilde{\gamma}_1 = \tilde{\gamma}_1 \frac{2}{\pi} arccos\left(cos\left(\pi f(\tilde{\gamma}_1)/2\right)^{\Omega} \right) \tag{5}$$

4) Power, where $\Omega \in (0, +\infty)$

$$\tilde{\gamma}_1^{\Omega} = \tilde{\gamma}_1 \frac{2}{\pi} arcsin\left(sin\left(\pi f(\tilde{\gamma}_1)/2\right)^{\Omega} \right) \tag{6}$$

4.1. Fuzzy sine trigonometry based LMAW method

The following section presents the fuzzy sine trigonometry logarithmic method of the additive weights model (fuzzy ST-LMAW). Fuzzy ST-LMAW represents improving the basic LMAW method (Pamucar et al., 2021) by applying non-linear functions of sine trigonometry. The presented fuzzy ST-LMAW methodology enables an objective and rational presentation of expert preferences with the possibility of consistently viewing the relationships between criteria. Within the fuzzy ST-LMAW framework, aggregation sine functions have been implemented to enable the fusion of expert preferences with adequate consideration of uncertainty in information using fuzzy sets (Zadeh, 1975). Sine trigonometry functions were used because they objectively present information around the origin. In the following part, the basic mathematical settings of the fuzzy ST-LMAW model are presented:

Step 1: Defining the priority vector through the prioritization of expert preferences. Let's assume that s experts represented by the set $R_i(i = 1, 2, \ldots, s)$ participate in the research and that a fuzzy scale with l fuzzy linguistic descriptors is predefined. Then, for a set of n criteria $C_j(j = 1, 2, \ldots, n)$ we can define a fuzzy priority vector $\mathbb{C}^g = \left(\tilde{\theta}^g_{(C_1)}, \tilde{\theta}^g_{(C_2)}, \ldots, \tilde{\theta}^g_{(C_n)}\right)(1 \le g \le s)$, where $\tilde{\theta}^g_{(C_n)} = \left(\tilde{\theta}^{g(l)}_{(C_n)}, \tilde{\theta}^{g(m)}_{(C_n)}, \ldots, \tilde{\theta}^{g(u)}_{(C_n)}\right)$ represents the importance of the nth criterion defined by the eth expert.

Step 2: Defining the fuzzy relationship vector. Based on the fuzzy priority vector and the absolute anti-ideal point (AAIP), the elements of the fuzzy ratio vector are defined. AAIP is defined based on condition $0 < \tilde{\upsilon} < \min\limits_{1 \le l \le p}\left(\tilde{\theta}_p\right)$. Based on the defined value of AAIP (υ) and the fuzzy priority vector, using expression Eq. (7), we can define the ratio vector $\mathbb{Z}^g = \left(\tilde{\varpi}^g_{(C_1)}, \tilde{\varpi}^g_{(C_2)}, \ldots, \tilde{\varpi}^g_{(C_n)}\right)(1 \le g \le s)$.

$$\tilde{\varpi}^g_{C_j} = \frac{\tilde{\theta}^g_{(C_j)}}{\tilde{\upsilon}} \tag{7}$$

where $\tilde{\theta}^g_{(C_j)} \in \mathbb{C}^g$

Step 3: Based on expert preferences, expression Eq. (8) defines the vectors of weighting coefficients for each expert. The vector of weight coefficients for the gth expert $(1 \le g \le s)$ is defined by applying the fuzzy logarithmic additive function as follows:

$$\tilde{w}^g_j = \frac{ln\left(\tilde{\varpi}^g_{\Psi_j}\right)}{ln\left(\tilde{\zeta}^g_j\right)} \tag{8}$$

where the fuzzy value $\tilde{\zeta}^g_j$ is defined using the fuzzy sine trigonometric function, expression Eq. (9):

$$\begin{aligned}\tilde{\zeta}^g_j = {} & \left[\sum_{j=1}^{n} 2\tilde{\varpi}^g_j arcsin\left(\prod_{j=1}^{n}\left(sin\left(\frac{\pi f\left(\tilde{\varpi}^g_j\right)}{2}\right)^{1/n}\right)\right)\Big/\pi\right]^n = \\ & \left[\sum_{j=1}^{n} 2\tilde{\varpi}^{g(l)}_j arcsin\left(\prod_{j=1}^{n}\left(sin\left(\frac{\pi f\left(\tilde{\varpi}^{g(l)}_j\right)}{2}\right)^{1/n}\right)\right)\Big/\pi\right]^n, \\ & \left[\sum_{j=1}^{n} 2\tilde{\varpi}^{g(m)}_j arcsin\left(\prod_{j=1}^{n}\left(sin\left(\frac{\pi f\left(\tilde{\varpi}^{g(m)}_j\right)}{2}\right)^{1/n}\right)\right)\Big/\pi\right]^n, \\ & \left[\sum_{j=1}^{n} 2\tilde{\varpi}^{g(u)}_j arcsin\left(\prod_{j=1}^{n}\left(sin\left(\frac{\pi f\left(\tilde{\varpi}^{g(u)}_j\right)}{2}\right)^{1/n}\right)\right)\Big/\pi\right]^n\end{aligned} \tag{9}$$

where $\tilde{\zeta}^e_j \in \mathbb{Q}^e$, $f\left(\tilde{\zeta}^e_j\right) = \tilde{\zeta}^e_j \big/ \sum_{j=1}^{n} \tilde{\zeta}^e_j$, $1 \le e \le h$ and n represents the number of criteria.

The aggregated fuzzy vector of weighting coefficients $\tilde{w}_j = \left(\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n\right)^T$ is defined using the expression Eq. (10) as follows:

$$\begin{aligned}\tilde{w}_j = {} & \left(w^{(l)}_j, (w^{(m)}_j, (w^{(u)}_j\right) = \\ & \sum_{d=1}^{s} 2w^{(l)d}_j arcsin\left(\prod_{d=1}^{s}\left(sin\left(\frac{\pi f\left(w^{(l)d}_j\right)}{2}\right)^{w_d}\right)\right)\Big/\pi, \\ & \sum_{d=1}^{s} 2w^{(m)d}_j arcsin\left(\prod_{d=1}^{s}\left(sin\left(\frac{\pi f\left(w^{(m)d}_j\right)}{2}\right)^{w_d}\right)\right)\Big/\pi, \\ & \sum_{d=1}^{s} 2w^{(u)d}_j arcsin\left(\prod_{d=1}^{s}\left(sin\left(\frac{\pi f\left(w^{(u)d}_j\right)}{2}\right)^{w_d}\right)\right)\Big/\pi\end{aligned} \tag{10}$$

where $\tilde{w}^d_j(d = 1, 2, \ldots, s)$ represents the expert's weight coefficient.

4.2. Fuzzy sine trigonometric based COPRAS method

The COmplex PRoportional ASsessment (COPRAS) method is one of decision making techniques improved by (Zavadskas et al., 1994) to assess the maximizing and minimizing index values. Fuzzy sine trigonometric norms are combined into the proposed models. The steps of Fuzzy Sine Trigonometric based COPRAS model are as follows:

Step 1: The home matrix is found with the help of Eqs. (11)–(12) according to expert opinions $(\alpha_e)(e = 1, 2, \ldots, \ell)$ for each alternative (χ_i)(i=1,2,…,m) in terms of criteria (φ_j)(j=1,2,…,n). Eq. (11) defines the initial decision matrix.

$$\eth_e = \left(\tilde{\Psi}_{ije}\right)_{n\times m} = \begin{array}{c c} & \begin{array}{cccc} \chi_1 & \chi_2 & \cdots & \chi_m \end{array} \\ \begin{array}{c} \varphi_1 \\ \varphi_2 \\ \vdots \\ \varphi_n \end{array} & \begin{pmatrix} \tilde{\Psi}_{11e} & \tilde{\Psi}_{12e} & \cdots & \tilde{\Psi}_{1me} \\ \tilde{\Psi}_{21e} & \tilde{\Psi}_{22e} & \cdots & \tilde{\Psi}_{2me} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{\Psi}_{n1e} & \tilde{\Psi}_{n2e} & \cdots & \tilde{\Psi}_{nme} \end{pmatrix} \end{array}, \tag{11}$$

where n and m indicate the number of decision criteria $(j = 1, 2, \ldots, n)$ and the number of alternative $(i = 1, 2, \ldots, m)$.

Later the aggregated the initial decision matrix is computed as follows:

$$\phi^e_{ij} = \left(\phi^{(\varepsilon)e}_{ij}, \phi^{(\lambda)e}_{ij}, \phi^{(\mu)e}_{ij}\right)$$

$$= \left[\begin{array}{l} \sum_{i=1}^{m} \tilde{\phi}^{(\varepsilon)e}_{ij} \frac{2}{\pi} arcsin\left(\prod_{i=1}^{m}\left(sin\left(\frac{\pi f\left(\tilde{\psi}^{(\varepsilon)e}_{ij}\right)^{1/m}}{2}\right)\right)\right)^m, \\ \sum_{i=1}^{m} \tilde{\phi}^{(\lambda)e}_{ij} \frac{2}{\pi} arcsin\left(\prod_{i=1}^{m}\left(sin\left(\frac{\pi f\left(\tilde{\psi}^{(\lambda)e}_{ij}\right)^{1/m}}{2}\right)\right)\right)^m, \\ \sum_{i=1}^{m} \phi^{(\mu)e}_{j} \frac{2}{\pi} arcsin\left(\prod_{i=1}^{m}\left(sin\left(\frac{\pi f\left(\tilde{\psi}^{(\mu)e}_{ij}\right)^{1/m}}{2}\right)\right)\right)^m. \end{array}\right] \tag{12}$$

where $\left(\tilde{\psi}_{ij}\right) = \tilde{\psi}_{ij} \big/ \sum_{j=1}^{n} \tilde{\psi}_{ij}$.

Step 2: The alternatives' score values (Δ_i) under each criterion are obtained by:

$$\Delta_{ij} = \frac{\phi^{(\varepsilon)}_{ij} + 4 * \phi^{(\lambda)}_{ij} + \phi^{(\mu)}_{ij}}{6} \tag{13}$$

Step 3: The score values of alternatives are normalized with the help of Eq. (14):

$$\eta_{ij} = \frac{\sum_{j=1}^{n} \Delta_{ij}}{n} \tag{14}$$

Step 4: The weighted normalized matrix is obtained.

$$S = \delta_{ij} = w_j \times \eta_{ij} \tag{15}$$

where w_j denotes the weight of the j^{th} criterion and δ_{ij} denotes the value of weighted normalized matrix.

Step 5: Sums B_i of attributes values for beneficial criteria are defined by:

$$B_i = \sum_{j=1}^{r} \delta_{ij} \tag{16}$$

where r represents number of benefit attributes.

Step 6: Sums C_i of attributes values for cost criteria are calculated by:

$$C_i = \sum_{j=r+1}^{n} \delta_{ij} \tag{17}$$

where $(n-r)$ represents number of cost attributes which.

Step 7: The minimal value of C_i is defined as follows:

$$C_{min} = minC_i \tag{18}$$

Step 8: The relative weight of each alternative ζ_i and Y_i is found by Eqs. (19) and (20):

$$\zeta_i = B_i + \frac{C_{min}\sum_{i=1}^{m} C_i}{C_i \sum_{i=1}^{m} \frac{C_{min}}{C_i}} \tag{19}$$

$$Y_i = \frac{\zeta_i}{max\zeta_i} \tag{20}$$

Later, alternatives are ranked according to their Y_i score from higher values to lower values.

5. Case study and results

5.1. Application of the fuzzy ST-LMAW method for defining weight coefficients of criteria

The following part presents the application of the fuzzy ST-LMAW method for defining the weighting coefficients of the criteria presented in Table 4.

Step: 1 Four experts evaluated the criteria using the fuzzy scale presented in Table 3.

The experts' preferences are represented within the vector of experts' priorities Table 5.

Table 3
Fuzzy linguistic terms and their corresponding values (Deveci et al., 2022).

Linguistic terms	Linguistic values of triangular fuzzy numbers
Absolutely low (AL)	(1, 1.5, 2.5)
Very low (VL)	(1.5, 2.5, 3.5)
Low (L)	(2.5, 3.5, 4.5)
Medium-low (ML)	(3.5, 4.5, 5.5)
Equal (E)	(4.5, 5.5, 6.5)
Medium-high (MH)	(5.5, 6.5, 7.5)
High (H)	(6.5, 7.5, 8.5)
Very high (VH)	(7.5, 8.5, 9.5)
Absolutely high (AH)	(8.5, 9, 10)

Table 4
The criteria list of Health DLT.

Main-criteria	Sub-criteria	Types
C1	Technological Maturity	Benefit
C2	Interoperability	Benefit
C3	Scalability	Benefit
C4	Transaction Speed	Benefit
C5	Cybersecurity and Digital Privacy	Cost
C6	Economic Feasibility	Benefit
C7	Energy and Resources Consumption	Cost
C8	Contribution to United Nations Sustainable Development Goals	Benefit
C9	Governance Aspects: Policy, Legal, Legislative Elements and Cyber Ethics	Benefit
C10	Industrial Standardization	Benefit

Table 5
Priority vectors of experts.

Criteria	Expert 1	Expert 2	Expert 3	Expert 4
C1	VH	VH	MH	VH
C2	H	H	VH	H
C3	VH	H	H	H
C4	ML	E	MH	ML
C5	VH	VH	AH	VH
C6	MH	E	H	E
C7	MH	MH	MH	H
C8	E	H	VH	MH
C9	H	H	H	H
C10	H	VH	VH	VH

Table 6
Ratio vectors.

Crit.	Expert 1	Expert 2	Expert 3	Expert 4
C1	(11.67,16,22.5)	(11.67,16,22.5)	(8.33,12,17.5)	(11.67,16,22.5)
C2	(10,14,20)	(10,14,20)	(11.67,16,22.5)	(10,14,20)
C3	(11.67,16,22.5)	(10,14,20)	(10,14,20)	(10,14,20)
C4	(5,8,12.5)	(5,8,12.5)	(5,8,12.5)	(5,8,12.5)
C5	(11.67,16,22.5)	(11.67,16,22.5)	(13.33,18,22.5)	(11.67,16,22.5)
C6	(8.33,12,17.5)	(6.67,10,15)	(10,14,20)	(6.67,10,15)
C7	(8.33,12,17.5)	(8.33,12,17.5)	(8.33,12,17.5)	(10,14,20)
C8	(6.67,10,15)	(6.67,10,15)	(10,14,20)	(8.33,12,17.5)
C9	(10,14,20)	(10,14,20)	(10,14,20)	(10,14,20)
C10	(10,14,20)	(11.67,16,22.5)	(10,14,20)	(11.67,16,22.5)

Step: 2 The experts' ratio vectors (see Table 6) are defined by applying expression (1) and represent the relationship between the elements of the priority vector (see Table 5) and AAIP. The fuzzy value $\tilde{\upsilon} = (0.4, 0.5, 0.6)$ was adopted to define the ratio vector (see Table 6). The value is adopted based on the condition $0 < \tilde{\upsilon} < \min_{1\le l\le p}(\tilde{\vartheta}_p)$, where $\tilde{\upsilon} \in]0, 1[$.

Step: 3 By applying expressions (2) and (3) and ratio vectors (see Table 6), fuzzy vectors of weight coefficients for each expert were defined. Thus, four weighting coefficient vectors were defined and aggregated using expression (4).

The weight coefficient for criterion C1 for the first expert is defined by applying expression (2):

$$W_{C_1} = \frac{ln(11.67, 16.00, 22.50)}{ln(3658\cdot 10^8, 1290\cdot 10^9, 5219\cdot 10^{10})}$$

$$\zeta_{C_1} = \frac{ln(12, 14, 16)}{ln(176\cdot 10^8, 1327\cdot 10^8, 5111\cdot 10^8)} = (0.084, 0.108, 0.141)$$

Where is the left fuzzy value for $ln(176\cdot 10^8, 1327\cdot 10^8, 5111\cdot 10^8)$ is defined by applying expression (3) as follows:

$$ln(\zeta_{C_1}^{1(l)}) = \left(93,33\frac{2}{\pi}arcsin \times \left(\begin{bmatrix} sin\left(\frac{\pi\cdot 0.13}{2}\right)^{1/10}\cdot sin\left(\frac{\pi\cdot 0.11}{2}\right)^{1/10}\cdot sin\left(\frac{\pi\cdot 0.13}{2}\right)^{1/10}\cdot \ldots\cdot \\ sin\left(\frac{\pi\cdot 0.07}{2}\right)^{1/10}\cdot sin\left(\frac{\pi\cdot 0.11}{2}\right)^{1/10}\cdot sin\left(\frac{\pi\cdot 0.11}{2}\right)^{1/10}\end{bmatrix}\right)^{10} = 176\cdot 10^8$$

Calculation of modal and upper values of $\tilde{\zeta}_{C1}^{1} = \left(\zeta_{C1}^{1(l)}, \zeta_{C1}^{1(m)}, \zeta_{C1}^{1(u)}\right)$ are calculated in a similar way.

In Table 7, the crisp values of the weighting coefficients are determined based on mathematical expectations and under the assumption that the fuzzy functions are subject to the β distribution. Fig. 1 shows graphically the fuzzy values of the weighting coefficients of the criteria.

Based on the defined fuzzy weights of criteria from Fig. 1, we can conclude that criteria C_5 and C_{10} are most important in the decision-making model. In contrast, criteria C_4 and C_6 have the least influence.

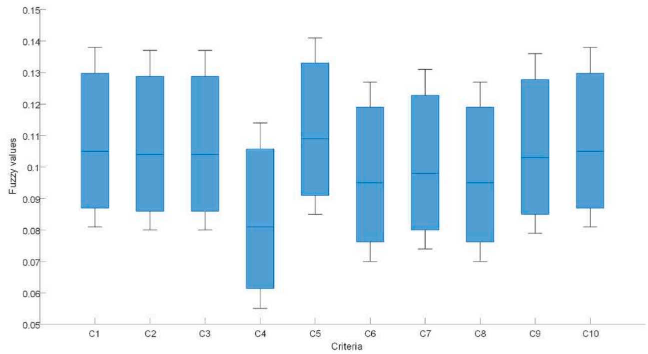

Fig. 1. Fuzzy weight coefficients of criteria.

5.2. Application of the fuzzy sine trigonometry based COPRAS method for assessment of alternatives

The Fuzzy Sine Trigonometry-based COPRAS method was employed to assess nine different health use cases where Distributed Ledger Technology (DLT) could be utilized. These alternatives were evaluated against ten criteria. The proposed decision-making method, supported by expert surveys, effectively identified and prioritized the best alternatives in terms of ranking.

The linguistic assessments of each alternatives under each criterion are given in Table 8.

Table 7
Aggregated fuzzy vector of weight coefficients.

Criteria	Fuzzy value	Crips values
C1	(0.081,0.105,0.138)	0.107
C2	(0.080,0.104,0.137)	0.106
C3	(0.080,0.104,0.137)	0.106
C4	(0.055,0.081,0.114)	0.082
C5	(0.085,0.109,0.141)	0.110
C6	(0.070,0.095,0.127)	0.096
C7	(0.074,0.098,0.131)	0.100
C8	(0.070,0.095,0.127)	0.096
C9	(0.079,0.103,0.136)	0.104
C10	(0.081,0.105,0.138)	0.107

Table 8
Expert opinions of alternatives.

Expert 1	Expert 2
(AH,H,MH,E,VH,MH,MH,MH,MH)	(E,ML,MH,E,VH,ML,ML,L,L)
(MH,MH,MH,E,MH,MH,MH,E,E)	(H,ML,MH,VL,E,L,E,L,L)
(AH,H,VH,H,VH,VH,VH,VH,VH)	(H,H,VH,H,H,VH,VH,H,H)
(VH,H,VH,VH,H,VH,VH,VH,VH)	(MH,H,H,VH,H,H,VH,MH,MH)
(AH,VH,VH,VH,VH,VH,VH,H,H)	(AH,VH,H,AH,AH,VH,H,VH,H)
(VH,VH,VH,VH,VH,VH,MH,VH,H)	(MH,VH,AH,MH,E,H,MH,VH,H)
(E,E,E,E,H,E,E,E,E)	(L,E,MH,MH,H,E,ML,MH,MH)
(H,H,E,MH,H,MH,MH,E,E)	(H,VH,E,E,H,VH,MH,VH,VH)
(VH,H,H,MH,MH,MH,H,MH,E)	(VH,VH,VH,MH,MH,E,MH,E,MH)
(H,H,MH,MH,MH,MH,MH,E,MH)	(VH,VH,MH,E,E,MH,MH,ML,ML)
Expert 3	**Expert 4**
(MH,E,H,MH,E,H,MH,MH,MH)	(VH,MH,MH,MH,VH,E,MH,VH,H)
(VH,H,AH,VH,VH,AH,AH,AH,VH)	(H,H,MH,ML,E,E,H,H,H)
(E,E,H,H,H,H,H,VH,H)	(H,MH,H,MH,H,H,VH,H,MH)
(ML,ML,H,MH,MH,H,H,H,MH)	(MH,ML,E,ML,E,ML,MH,E,E)
(AH,AH,AH,AH,AH,AH,AH,AH,AH)	(AH,H,H,AH,AH,VH,AH,VH,H)
(H,H,VH,H,H,VH,H,VH,H)	(MH,E,MH,MH,E,H,MH,MH,H)
(E,E,H,H,MH,MH,MH,MH,H)	(H,H,MH,MH,H,E,H,H,MH)
(VH,VH,VH,VH,VH,VH,VH,VH,VH)	(H,MH,E,E,H,MH,MH,VH,MH)
(MH,MH,H,H,H,H,H,H,H)	(VH,H,VH,MH,MH,MH,H,H,MH)
(H,H,AH,VH,VH,VH,VH,VH,VH)	(AH,VH,MH,E,H,MH,H,H,E)

Step 1: To find the home matrix, the expert opinions are aggregated using Tables 8 and 3, and Eqs. (11)-(12). The home matrix is provided in Table 9.

Step 2: The score values of the alternatives in terms of each criteria is calculated by Eq. (13). The score values is given in Table 10.

Step 3: The score values of the alternatives in terms of each criteria is normalized using Eq. (14) and is reported in Table 11.

Step 4: The weighted normalized matrix is obtained with the help of Eq. (15) and is presented in Table 12.

Step 5: Sums B_i of attributes values for beneficial criteria are computed using Eq. (16) and is provided in Table 13.

Step 6: Sums C_i of attributes values for cost criteria are computed using Eq. (17) and is provided in Table 13.

Step 7: The minimal value of C_i is determined by Eq. (18) and is given in Table 13.

Step 8: The relative weight of each alternative ζ_i and Y_i is calculated by Eqs. (19) and (20) and are reported in Table 13.

The rank of nine alternatives is $A1 > A3 > A7 > A5 > A6 > A2 > A4 > A8 > A9$.

5.3. Sensitivity analysis and validation of the results

The following section presents the sensitivity analysis of the presented multi-criteria framework, and the results are validated. As part of the sensitivity analysis, subjectively defined parameters were considered, and whether other parameter values from the permissible interval affected the change of the initial results were analyzed. Within the proposed MCMD methodology, most input parameters are defined using consensus and are not subject to change, except for the AAIP value, which is defined based on the condition $0 < \tilde{\upsilon} < \min_{1\le l\le p}\left(\tilde{\theta}_p\right)$. AAIP is used within the fuzzy ST-LMAW method to define the ratio vector and impacts the final values of the weighting coefficients of the criteria.

The initial values of the weighting coefficients of the criteria are defined for the value $\tilde{\upsilon} = (0.4, 0.5, 0.6)$. The adopted value AAIP is defined based on the condition $\tilde{\upsilon} \in \left]0,1\right[$ and is chosen because it is in the middle of the interval $\left]0,1\right[$. To validate the results, 50 scenarios were created to simulate the AAIP change within the allowed values from the interval $\tilde{\upsilon} \in \left]0,1\right[$. In the first scenario, a value of 0.01 was adopted, while in each subsequent scenario, the value was increased by 0.02. Thus, the AAIP value of 0.99 was adopted in the last fiftieth scenario.

For each AAIP change, a new fuzzy vector of weight coefficients was generated in each scenario. Thus, fifty new fuzzy vectors of weighting coefficients were generated. The changes in fuzzy weight coefficients that occurred due to the change of AAIP during 50 scenarios are presented in Fig. 2.

From Fig. 2, we can see that the variations of the AAIP values affect the changes in the values of the weighting coefficients of the criteria. It is observed that the changes in AAIP affect the reduction of the left limit value of the fuzzy weights of criteria. At the same time, they affect the increase of the right limit values of the fuzzy weight coefficients of the criterion. Such changes also affect the significance of the criteria since there is a shift in the interval values of the weighting coefficients.

In the next step of the sensitivity analysis, 50 vectors of weighting coefficients were used as input parameters in the fuzzy sine trigonometric-based COPRAS model. The influence of the input parameters on the output values of the score functions of individual alternatives in the fuzzy sine trigonometric-based COPRAS model is shown in Fig. 3.

Fig. 3 shows alternatives A_1, A_2, A_3 and A_9 score functions. Based on the presented results (see Fig. 3), the change in AAIP in the interval $\tilde{\upsilon} \in \left]0,1\right[$ causes fewer changes in the core functions of the alternatives. Similar changes in score functions occur with the remaining alternatives, which is confirmed in Fig. 4.

Fig. 4 confirms that AAIP affects changes in score functions. However, these changes are not drastic enough to predict changes in initial

Table 9
The initial matrix.

Alternatives	C1	C2	C3	C4	C5
A1	(6.28,7.22,8.24)	(6.46,7.46,8.47)	(6.32,7.25,8.27)	(5.29,6.32,7.35)	(8.5,9,10)
A2	(4.86,5.88,6.9)	(5.32,6.36,7.38)	(5.68,6.69,7.7)	(4.75,5.79,6.82)	(7.46,8.35,9.36)
A3	(5.73,6.74,7.74)	(6.12,7.04,8.05)	(6.98,7.98,8.98)	(6.13,7.15,8.16)	(7.2,8.1,9.1)
A4	(4.97,5.98,6.98)	(3.6,4.74,5.83)	(6.23,7.23,8.24)	(5.71,6.76,7.79)	(8.24,8.87,9.87)
A5	(6.59,7.61,8.63)	(5.36,6.38,7.4)	(6.74,7.74,8.74)	(5.68,6.69,7.7)	(8.24,8.87,9.87)
A6	(4.86,5.88,6.9)	(4.74,5.76,6.81)	(6.98,7.98,8.98)	(5.75,6.79,7.82)	(7.74,8.62,9.62)
A7	(4.9,5.92,6.93)	(6.06,7,8.01)	(7.23,8.24,9.24)	(6.69,7.7,8.7)	(7.7,8.47,9.48)
A8	(4.85,5.93,6.98)	(4.95,5.97,7.03)	(6.98,7.98,8.98)	(5.88,6.9,7.91)	(7.46,8.35,9.36)
A9	(4.68,5.75,6.79)	(4.8,5.89,6.94)	(6.46,7.46,8.47)	(5.64,6.66,7.67)	(6.95,7.85,8.85)
Alternatives	**C6**	**C7**	**C8**	**C9**	**C10**
A1	(6.19,7.2,8.2)	(4.24,5.29,6.32)	(6.74,7.74,8.74)	(6.93,7.94,8.95)	(7.2,8.1,9.1)
A2	(6.36,7.38,8.39)	(4.93,5.94,6.95)	(6.69,7.7,8.7)	(6.46,7.46,8.47)	(6.98,7.98,8.98)
A3	(7.15,8.06,9.06)	(5.45,6.46,7.46)	(5.1,6.12,7.13)	(6.98,7.98,8.98)	(6.12,7.04,8.05)
A4	(6.19,7.2,8.2)	(5.45,6.46,7.46)	(5.36,6.38,7.4)	(5.73,6.74,7.74)	(5.36,6.38,7.4)
A5	(5.59,6.61,7.63)	(6.23,7.23,8.24)	(6.74,7.74,8.74)	(5.73,6.74,7.74)	(5.88,6.9,7.91)
A6	(6.98,7.98,8.98)	(4.73,5.73,6.74)	(6.41,7.43,8.43)	(5.45,6.46,7.46)	(5.94,6.95,7.95)
A7	(5.73,6.74,7.74)	(4.86,5.88,6.9)	(5.94,6.95,7.95)	(6.23,7.23,8.24)	(6.19,7.2,8.2)
A8	(6.93,7.94,8.95)	(5.45,6.46,7.46)	(6.59,7.61,8.63)	(5.68,6.69,7.7)	(5.24,6.28,7.31)
A9	(6.5,7.5,8.5)	(5.45,6.46,7.46)	(6.09,7.12,8.13)	(5.45,6.46,7.46)	(5.03,6.06,7.09)

Table 10
The score values.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	7.23	7.46	7.27	6.32	9.08	7.20	5.29	7.74	7.94	8.11
A2	5.88	6.35	6.69	5.79	8.37	7.38	5.94	7.70	7.46	7.98
A3	6.74	7.06	7.98	7.15	8.11	8.07	6.46	6.12	7.98	7.06
A4	5.98	4.73	7.23	6.76	8.93	7.20	6.46	6.38	6.74	6.38
A5	7.61	6.38	7.74	6.69	8.93	6.61	7.23	7.74	6.74	6.90
A6	5.88	5.77	7.98	6.79	8.64	7.98	5.73	7.43	6.46	6.94
A7	5.92	7.01	8.24	7.70	8.51	6.74	5.88	6.94	7.23	7.20
A8	5.92	5.97	7.98	6.90	8.37	7.94	6.46	7.61	6.69	6.28
A9	5.75	5.88	7.46	6.66	7.86	7.50	6.46	7.12	6.46	6.06

Table 11
The normalized values.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.13	0.13	0.11	0.10	0.12	0.11	0.09	0.12	0.12	0.13
A2	0.10	0.11	0.10	0.10	0.11	0.11	0.11	0.12	0.12	0.13
A3	0.12	0.12	0.12	0.12	0.11	0.12	0.12	0.09	0.13	0.11
A4	0.11	0.08	0.11	0.11	0.12	0.11	0.12	0.10	0.11	0.10
A5	0.13	0.11	0.11	0.11	0.12	0.10	0.13	0.12	0.11	0.11
A6	0.10	0.10	0.12	0.11	0.11	0.12	0.10	0.11	0.10	0.11
A7	0.10	0.12	0.12	0.13	0.11	0.10	0.11	0.11	0.11	0.11
A8	0.10	0.11	0.12	0.11	0.11	0.12	0.12	0.12	0.11	0.10
A9	0.10	0.10	0.11	0.11	0.10	0.11	0.12	0.11	0.10	0.10

Table 12
The weighted normalized matrix.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.013	0.014	0.011	0.009	0.013	0.010	0.009	0.012	0.013	0.014
A2	0.011	0.012	0.010	0.008	0.012	0.010	0.010	0.012	0.012	0.014
A3	0.012	0.013	0.012	0.010	0.012	0.011	0.011	0.009	0.013	0.012
A4	0.011	0.009	0.011	0.010	0.013	0.010	0.011	0.010	0.011	0.011
A5	0.014	0.012	0.012	0.010	0.013	0.009	0.013	0.012	0.011	0.012
A6	0.011	0.011	0.012	0.010	0.012	0.011	0.010	0.011	0.010	0.012
A7	0.011	0.013	0.013	0.011	0.012	0.010	0.010	0.011	0.012	0.012
A8	0.011	0.011	0.012	0.010	0.012	0.011	0.011	0.012	0.011	0.011
A9	0.011	0.011	0.011	0.010	0.011	0.011	0.011	0.011	0.010	0.010

ranks. The results confirm that alternative A_1 represents the best solution from the considered set and has a distinct advantage compared to the remaining alternatives. Also, the results from Fig. 4 confirm that alternative A_3 represents the second-ranked option, while alternatives A_8 and A_9 represent the worst solutions within the considered alternatives. Based on the presented results, we can conclude that the initial solution is validated and that the initial ranking is credible.

5.4. Comparations with existing prioritization frameworks

The following part presents the validation of the proposed fuzzy ST-COPRAS methodology with other approaches for DLT prioritization. Since a few studies consider the application of MCDM techniques for prioritizing DLTs in healthcare, MCDM techniques initially used in the literature for evaluating DLTs from other areas, such as the energy and

Table 13
The output of the model.

	B_i	C_i	ζ_i	Y_i	Ranking
A1	0.096	0.022	0.120	100 %	1
A2	0.043	0.022	0.067	55.81 %	6
A3	0.047	0.023	0.070	58.68 %	2
A4	0.044	0.024	0.066	55.38 %	7
A5	0.047	0.025	0.068	56.83 %	4
A6	0.043	0.022	0.067	55.95 %	5
A7	0.046	0.022	0.069	57.92 %	3
A8	0.044	0.023	0.066	55.38 %	8
A9	0.042	0.023	0.065	54.51 %	9

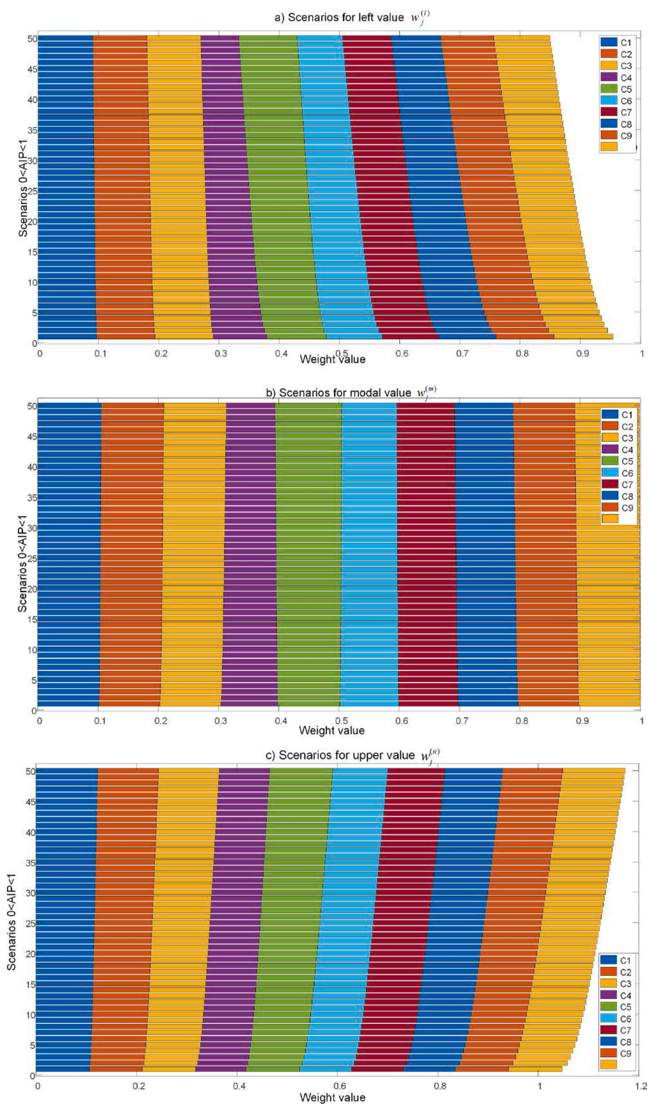

Fig. 2. Changes in weighting coefficients of criteria during 50 scenarios.

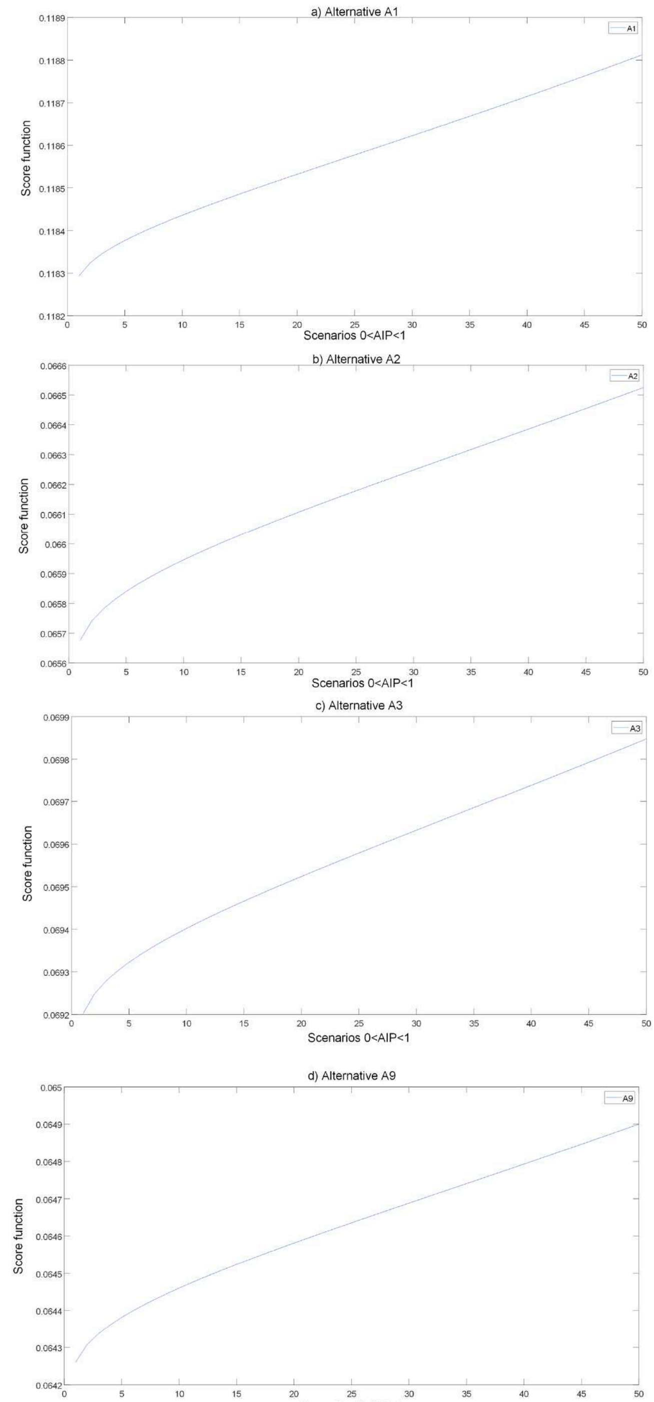

Fig. 3. The influence of AAIP on the change of score functions of alternatives.

manufacturing industry, were selected for validation. Since these models have a high degree of generalization, this fact does not diminish the results presented in this section. Three models were used for comparison as follows: 1) fuzzy type-2 neutrosophic Evaluation based on Distance from Average Solution (EDAS) method (Cali et al., 2022), 2) Fuzzy linear evaluation model based on the application of the Ordinal Priority Approach (fuzzy OPA) (Sadeghi et al., 2023) and 3) Hybrid models for prioritizing DLTs based on the application of AHP and CoCoSo methods (Matey et al., 2025).

The application of these models is shown under the same conditions and on the same data set, with minor adjustments that depend on the uncertainty theory applied within the applied mathematical models. Fig. 5 indicates the results obtained by applying the mentioned multi-criteria techniques.

The results from Fig. 5 show a high degree of agreement within the applied multi-criteria techniques. This is also confirmed by Spearman's correlation coefficient, which is 0.979, which indicates an extremely high degree of correlation. From Fig. 5, we can see a complete correlation between the fuzzy ST-COPRAS model and the AHP-CoCoSo methodology. At the same time, there are minor deviations in the ranks compared to the fuzzy OPA and fuzzy type-2 neutrosophic EDAS.

Such minimal deviations are expected since these are models that are based on different mathematical concepts, prioritization, and

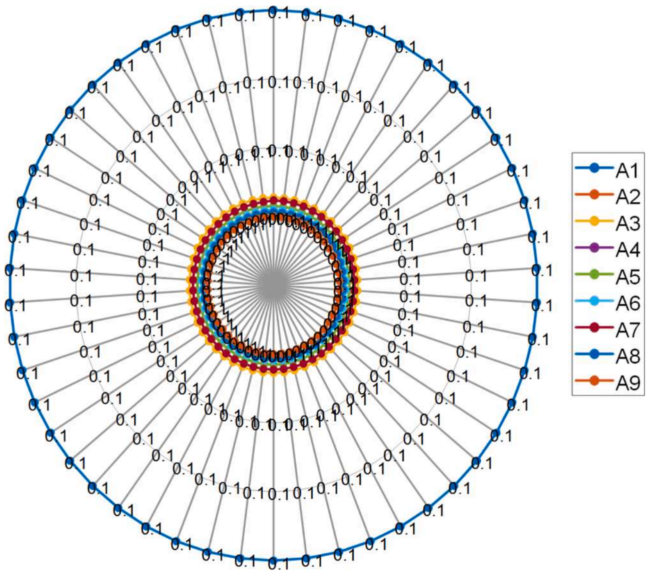

Fig. 4. Comparative presentation of the change in the score functions of the alternatives during 50 scenarios.

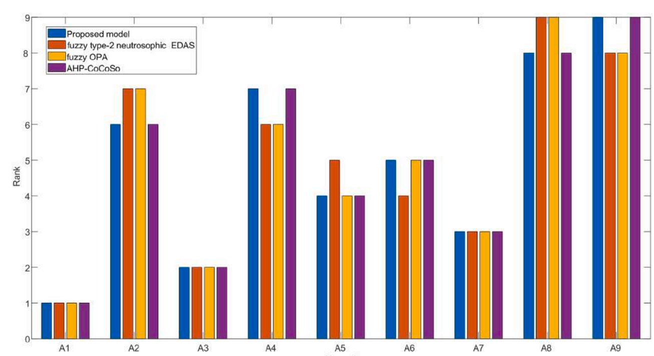

Fig. 5. Comparisons with existing prioritization frameworks.

uncertainty processing in information. For example, the fuzzy OPA concept applies linear programming with predefined priorities of alternatives and criteria to compare DLTs. This approach requires adapting the original data set to the model's requirements, which can lead to less distortion of the data structure. Similar deviations appear with the fuzzy type-2 neutrosophic EDAS methodology, which is also a consequence of applying the hybrid fuzzy type-2 neutrosophic approach for uncertainty processing. This is confirmed by using the fuzzy EDAS methodology since the results obtained are in full correlation with the fuzzy ST-COPRAS model.

The comparison presented in Fig. 5 confirmed the initial results of the fuzzy ST-COPRAS model. In addition to the presented results, it is necessary to point out two key advantages of the fuzzy ST-COPRAS methodology in relation to the models that were used for comparison: i) One of the advantages of the fuzzy ST-COPRAS methodology is the adaptability and the possibility of variation of input parameters, primarily subjectively defined weighting coefficients. This characteristic allows the proposed methodology to be adapted to different scenarios that may appear due to uncertainty in information and dynamic environmental conditions. On the other hand, the models that were used for comparison do not have such adaptability, but predefined fixed values of weighting coefficients are used in the evaluation process; ii) Another advantage is the possibility of processing complex and uncertain information, which enables rational reasoning and objective presentation of information around the origin. On the other hand, the MCDM techniques used for comparison use a linear approach to information processing, which is a limitation when processing complex and uncertain information.

6. Discussion

This section provides some policy recommendations based on the ranking obtained by the model. A key takeaway is that policy makers should prioritize establishing regulatory frameworks and standards for the usage of DLT in EHR systems. These should cover data ownership, sharing, interoperability and patient-empowerment. Adoption of DLT in national or regional EHR should be encouraged. Another use case where DLT can make an impact is Pharmaceutical Supply Chain Management, especially in combating counterfeit drugs and ensuring product authenticity. Creating protocols for using DLT for transparency and accountability should also be high on policy makers‘ list. Health Insurance and Payment Settlement is another use case that scored high, in this area stakeholders can encourage the development and deployment of DLT-based insurance systems by establishing clear guidelines and security requirements.

Despite the clear advantages of DLT for healthcare-such as improved security, transparency, and data provenance – several non-technical obstacles may hinder its uptake. First, regulatory uncertainty remains significant: aligning decentralized ledgers with data protection regimes like GDPR (General Data Protection Regulation) in Europe or Health Insurance Portability and Accountability Act (HIPAA) in the U.S. is still an open challenge, and there is no unified global framework for health-specific DLT governance. Second, interoperability issues with existing electronic health record (EHR) systems create operational friction, as integrating blockchain platforms into legacy IT infrastructures often requires extensive customization and middleware. Third, stakeholder reluctance-driven by perceived complexity, up-front implementation costs, and uncertainty around return-on-investment ROI-can slow organizational decision-making and pilot adoption . Finally, lack of sufficient industry standards and governance bodies for clinical DLT deployments means trust and consensus frameworks are often ad hoc, further impeding large-scale roll-out. Addressing these barriers will be crucial for translating DLT's technical promise into real-world healthcare improvements.

The lower ranking of some DLT use cases is indicative of present and future challenges that need to be addressed before widespread adoption. In the area of medical device tracking and IoMTs scalability, energy consumption, and cybersecurity topics must be handled, so policy makers should prioritize innovation in these concerns. Also, instead of widespread adoption, a more phased implementation, with pilot testing, can better ensure patient safety. Similarly, in the case of interconnected smart health and elderly care, a more phased approach should be encouraged, mainly due to the vulnerabilities of these populations. Research in security, usability should be funded, to ensure fair access and understanding by patients with less digital skills.

7. Conclusion

In conclusion, this research has showcased the strong potential of Distributed Ledger Technology across a wide spectrum of healthcare applications. The introduction of the fuzzy ST-COPRAS model, a novel decision-making framework, has provided a structured approach to prioritize these varied health DLT use cases.

The prioritization of healthcare-related DLT use cases presented in this study goes beyond theoretical exploration; it delivers actionable insights for a wide range of stakeholders-including policymakers, healthcare providers, standardization bodies, and investors. By systematically evaluating use cases such as Electronic Health Records (EHR) management, clinical trial oversight, pharmaceutical supply chain tracking, IoMT integration, telemedicine, public health surveillance, insurance and payment settlement, smart health systems, and governance aspects, this research identifies the most impactful and feasible applications of

DLT in healthcare. The resulting prioritization framework offers a practical tool for strategic resource allocation and targeted investment, serving as a roadmap to guide innovation and accelerate the secure, ethical, and sustainable adoption of DLT across the healthcare ecosystem.

The findings of this research serve as a valuable guide for navigating the rapidly evolving landscape of health DLT. By embracing this technology and prioritizing its applications based on a rigorous and comprehensive evaluation framework, we can unlock the full potential of DLT to revolutionize healthcare, improve patient outcomes, and create a more equitable and sustainable healthcare system for all.

CRediT authorship contribution statement

Muhammet Deveci: Conceptualization, Methodology, Software, Writing – original draft. **Dragan Pamucar:** Methodology, Software, Validation, Writing – original draft. **Andrei Vasilateanu:** Conceptualization, Supervision, Writing – original draft, Reviewing. **Gora Datta:** Conceptualization, Supervision. **Nicolae Goga:** Conceptualization, Supervision, Validation, Writing – original draft. **Constantin Viorel Marian:** Validation, Writing – review & editing. **Ioan-Alexandru Bratosin:** Writing – original draft. **Umit Cali:** Conceptualization, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing.

Data availability

No data was used for the research described in the article.

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.

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