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RESEARCH

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Selection of data analytic techniques by using fuzzy AHP TOPSIS from a healthcare perspective

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Abstract

The healthcare industry has been put to test the need to manage enormous amounts of data provided by various sources, which are renowned for providing enormous quantities of heterogeneous information. The data are collected and analyzed with different Data Analytic (DA) and machine learning algorithm approaches. Researchers, scientists, and industrialists must manage or select the best approach associated with DA in healthcare. This scientific study is based on decision analysis between the DA factors and alternatives. The information affects the whole system in a rational manner. This information is very important in healthcare sector for appropriate prediction and analysis. The evaluation discusses its benefits and presents an analytic framework. The Fuzzy Analytic Hierarchy Process (Fuzzy AHP) approach is used to address the weight of the factors. The Fuzzy Techniques for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) address the rank of the data analytic alternatives used in healthcare sector. The models used in the article briefly discuss the challenges of DA and approaches to address those challenges. The assorted factors of DA are capture, cleaning, storage, security, stewardship, reporting, visualization, updating, sharing, and querying. The DA alternatives include descriptive, diagnostic, predictive, prescriptive, discovery, regression, cohort and inferential analyses. The most influential factors of the DA and the most suitable approach for the DA are evaluated. The 'cleaning' factor has the highest weight, and 'updating' is achieved at least by the Fuzzy-AHP approach. The regression approach of data analysis had the highest rank, and the diagnostic analysis had the lowest rank. Decision analyses are necessary for data scientists and medical providers to predict diseases appropriately in the healthcare domain. This analysis also revealed the cost benefits to hospitals.

Keywords Data analytics, Data analysis, Healthcare, Fuzzy AHP, Fuzzy TOPSIS

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Introduction

DA is the study of analyzing basic facts to draw conclusions using the Python programming language [1]. The DA technique can help a corporation streamline its presentation, work more efficiently, increase benefits, or pursue more focused decisions. The methods and processes of information research have been mechanized into computations and cycles that operate on unprocessed data for human use. In terms of prediction results, prescriptive analytics are one of several approaches for dealing with DA. Data analysis relies on a variety of software tools, including accounting sheets, information representations, revealing devices, information mining projects, and open-source languages [2]. The importance of DA may be attributed to the fact that it helps businesses enhance their displays. Implementing it in the plan of action suggests that businesses may help save costs by identifying more effective ways to complete tasks and a wealth of information. The DA tools and process are too expensive so such investigations are necessary. Decision making is an important task for selecting the most suitable approach for data analysis in the healthcare sector. The healthcare sector has vast quantities of big data that have the power to make or break a circumstance [3]. Due to the immense potential it possesses, it has been the focus of intense inquiry for the past twenty years. To enhance the services they offer, a multitude of public and private sector entities produce, retain, and evaluate vast quantities of data. In the healthcare industry, some hotspots for big data include clinical records, patient diagnosis records, clinical evaluation results, and Internet of Things (IoT) devices [4]. Additionally, biomedical research adds significantly to the mass of information about public health care. These data require legal management and analysis to presume significant facts [5]. The multi criteria decision analysis approach of fuzzy AHP TOPSIS is used for the analysis and to determine the weights with criteria of attributes. The DA attributes are the alternatives in this research article. The data were collected from different hospitals and medical colleges of Uttar Pradesh India for analysis. Large scale data analysis has become one of the most challenging projects in recent years for the healthcare sector. Suppliers that have just recently learned how to enter data into their records are now being contacted to extract important lessons from them. These lessons are then used for complex initiatives that directly affect suppliers' payback rates. The rewards may be enormous for medical care associations that successfully integrate information driven experiences into their clinical and functional cycles. Among the numerous benefits of converting information resources into information pieces of knowledge are better for patients, reduce healthcare expenses, more deceivability into execution, and improved staff and buyer fulfillment rates [6]. Despite this, the path to a major medical examination is not easy and is filled with obstacles to overcome. The expenses of the healthcare sector are shown in Fig. 1 [Health expenditure and financing (oecd.org)].

The Fig. 1 shows, the monetary expenses of different countries from 2016 to 2023. The proposed approaches are useful for the medical industry. The DA algorithms have many advantages and disadvantages, so the usefulness of the best approach is determined by expert opinion in this field. The opinions are selected on the basis of factors associated with DA, and the most suitable approach for DA is taken from the literature.

The structure of the article is arranged by the sections. In section two describes the related work on the analysis of DA and its approach. Further Sect. 3 materials and methods, elaborate on the hierarchy of DA and its factors

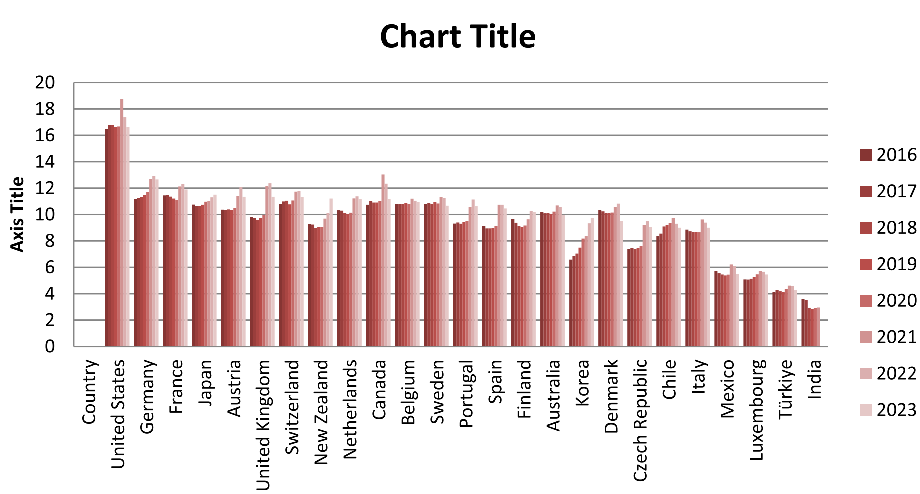

Fig. 1 Expenditure data for the healthcare sector from 2016 to 2023

according to different attributes, describe the methodology and its advantages for decision making, and describe the mathematical analysis and its values in the data analysis subsection. Section four compares the analysis with classical decision making algorithm with fuzzified decision making methods. Section 5 explains the sensitivity analysis and validates the results of the research analysis. Section 6 concludes the paper with the results of the analysis and Sect. 7 explains the conclusions of the research with future research and limitations.

Related works

Massive amounts of data analysis tools and procedures have been developed to handle these massive amounts of data in the clinical domain. Big data's effects on healthcare and the abundance of tools in the Hadoop environment [7]. We also look at the planned architecture of massive information analysis for health services, which encompasses the genetic dataset, electronic health records, text/symbolism, clinical decisions emotionally supported network, and information collection history of different branches. The issues are identified from the literature via data analysis.

In the medical service sector, [8] the use of massive data has grown to support the most widely used analysis methods of patients diagnosis and treatment delivery. To address a few crucial concerns ingrained in the massive information worldview, the medical services industry's acceptance and advancement of large amounts of information examination are still limited. These problems are resolved by focusing on the upcoming and promising fields of clinical investigation. A novel massive information examination method that makes use of an apache flash is also suggested [8]. Big Data Analysis (BDA) has the ability to continuously evaluate clinical data to support physicians' effective practices and focus on calm contemplation.

The BDA may modify the way medical service providers employ sophisticated innovations to compile data from their clinical and other information repositories and make error-free decisions [9]. As massive information assessments grow more commonplace, issues including guaranteeing safety, protecting security, establishing standards, organizing, and continuously addressing improvements and enhancements will garner more attention. When it comes to the guidelines for stage assessment, attributes like transparency, clarity, simplicity of use, flexibility, the ability to provide direction at different levels of detail, protection and security facilitation, and quality assurance should all be kept in mind. Open source stages contain the normal advantages and disadvantages, despite being the bulk of stages that are currently available for expansion. For long-term success, BDA in clinical benefits should be combined.

Currently, this study [10] appears to be useful for differentiating edges that are arranged according to different affiliation components. An examination of business professionals from the automotive, steel, car components manufacturing, and electrical stuff firms is conducted in order to establish a logical link between the obstacles. The scientific procedures used in this inquiry. Snags, or high driving power free variables, are important components that were further divided using fluffy AHP in order to assess their overall relevance [11].

The researcher Boutkhoum et al. mentioned that selecting the best solution for our extensive information projects is a complex problem in particular scenarios that necessitate a thorough evaluation approach. To assist customers in effectively selecting their preferred configuration, the hybrid approach satisfies these requirements in four stages. Using the fondness chart, a dynamic panel performs the differentiating proof of evaluation criteria in the main stage. Due to the varying significance of the selected standards, a fuzzy AHP cycle is applied in the second stage to assign the significance loads for each basis [12]. These weighted models are then used as inputs in the third stage of the fuzzy TOPSIS process to evaluate and gauge the presentation of each alternative [13]. The Yu et al. used significant information mining computations in light of fuzzy numerous leveled grouping examinations and semantic comparability relationship highlight extraction to incorporate examination and useful data extraction of large scope text data information. The computation makes use of fuzzy scientific pecking order cycle to determine the semantic proximity and relevance of a large amount of information and speculative planning to build a semantic concept tree [14]. The research article is arranged in section three to explain the framework of the research including the factors affecting DA in the healthcare sector and alternatives to the DA.

The researchers Ahmed et al. mention that the fuzzy AHP is a popular approach that may be applied to numerous problems when there are conflicting or ambiguous criteria. The conversion of human instinct into mathematical attributes is one of the central questions in fuzzy AHP. By incorporating loose data into fuzzy numbers, fuzzy AHP approaches address human tendencies while dressing the usual fuzzyness of human guidance. This work initiated a meticulous mathematical and experimental evaluation to determine if fuzzy numbers can accurately convey preferences and choices within the AHP system. The results of this investigation demonstrated that, on average, normal AHP approaches outperform previous fuzzy AHP methods in a substantial way [15].

Jawad et al. analyze and explain multi-criteria decision-making issues are solve by the use of proper techniques for evaluating and choosing stocks. The AHP is widely applied in operation management. The main feature of AHP is that it uses a critical scale to create pairwise correlations after first reducing the complex choice problems in various leveled configurations of objectives, measurements, sub-rules, and alternatives. The prototype of findings and a demonstration of the validity of the suggested strategy is provided by a portfolio selection [16]. The fuzzy AHP determines the impact of the factors. The weight of the plan is evaluated using the measurements of quantum choices through the dynamic computation of fuzzy AHP [17]. The researcher Yadav et al. mention fuzzy AHP is used to register their loads and strategies are then ranked according to how successfully they get over challenges using the fuzzy TOPSIS tool. The sensitivity analysis is used to evaluate the model's robustness. Three primary barriers are representatives' resistance, leaders' lack of accountability, and the absence of a clear boundary. Likewise, providing financial assistance, allocating funds for research and development, and providing specialized assistance are the most effective approaches to overcome these obstacles [18].

The Yaghoobi et al. assess and investigate with the application of fuzzy TOPSIS interaction to isolate and highlight the sections related to business information. This article lays forth a scientific method for improving business intelligence skills. The fuzzy TOPSIS approach was applied to address the inherent ambiguity and susceptibility of the data. Consequently, the fuzzy TOPSIS method was employed to place the essential components [19].

The Kazemi et al. investigate the key to a business's success is ensuring that it can control the market for a considerable amount of time with a variety of goods and services. Business insight is particularly useful in attaining this advantage because it makes it possible for the company to employ wise choices, copious amounts of data and research, and ongoing interaction development to sustain this benefit and create sustainable growth [20]. The research analysis ranks the factors that, from the perspective of business intelligence, influence reasonable upper hand. The research was using content analysis to derive markers from earlier research. Pointers were placed using the fuzzy TOPSIS method in the further phase [21].

Materials and methods

DA affecting factors and alternatives

The DA is a broad phrase that covers a variety of information research methods. Any type of data may be subjected to information examination techniques to gain knowledge that can be used to advance things. Procedures for information inspection can reveal patterns and metrics that would otherwise be lost in the volume of data. This information may then be used to improve cycles and increase a system's overall output. The research framework of DA is shown in Fig. 2. The DA approaches have the following steps.

Choosing the information requirements or the method of information gathering is the first stage. Age, segment, wage, or orientation can all be used to separate information. Information values might be categorical or mathematical [22]. The most typical method of acquiring information is the second step toward research. This should be achievable using a variety of tools, including computers, the internet, cameras, and natural resources [23]. After being acquired, the information must be organized so that it can be broken down. This might occur on a sheet or any piece of software that can accept true data [24]. The data are then organized before an inquiry. The data are then organized before an inquiry. The data were thoroughly examined and tested to ensure that there were no duplicates, errors, or inadequacies. Before a subject of the examination becomes an

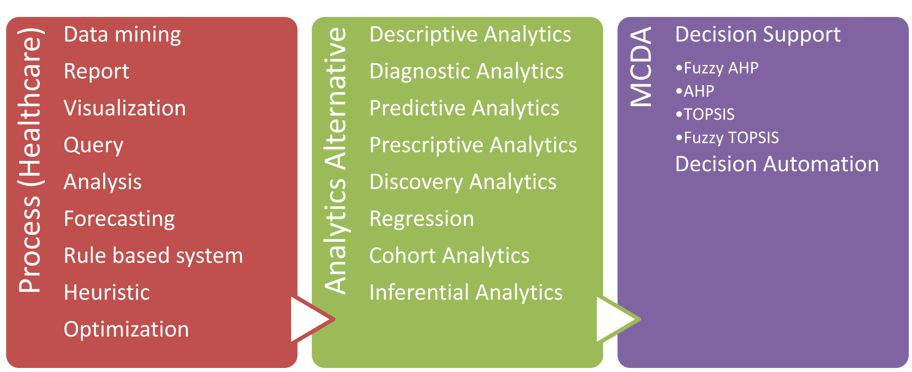

Fig. 2 Research framework for data analytics

information specialist, this stage corrects any errors [25]. DA approaches involve three major steps process, secondary analysis, and decision analysis via the fuzzy AHP TOPSIS technique.

For instance, manufacturing companies routinely track the runtime, idle time, and work queue for various machines before analyzing the data to determine the most likely arrangement of tasks to ensure that the machines operate closer to their maximum capacity [26]. DA is far more powerful than simply identifying existing blocks. DA is used by gaming companies to create reward programs for gamers that keep the majority of players actively playing. To keep you clicking, viewing, or rearranging content organizations use a lot of comparable DA to make you glad to acquire another look.

Data analytic factors in the healthcare sector

Capture [F1] the process of extracting data from an electronic or paper report that is organized or unstructured and transforming it into a computerized design that can be understood by machines is known as information capture [27]. Advances in the science of artificial intelligence, or computerized thinking, have made it easier than ever to access information [28]. The healthcare sector is a prime example of information being used. Information capture technology is used to extract data related to medications or medical equipment that is paid in transactions, as well as to automatically calculate the amount of stock remaining for those important items, ensuring a seamless flow of data in stock management. The factor and respective alternative hierarchy is shown in Fig. 3.

With respect to *Cleaning [F2],* the most popular method for correcting or removing inaccurate, damaged, improperly created, duplicate, or inadequate data within a dataset is information cleaning [29]. There are many incredible opportunities for information to be duplicated or mislabeled when connected to different information sources. Even if the findings and computations appear correct, they are inconsistent if the information is erroneous [4]. Given that the cycles in the information cleaning process will vary from dataset to dataset, there is no fixed methodology for advising the precise steps to take.

Storage [F3] Information storage, often known as information holding, is the process of storing data and making it as quickly available as possible through the use of specially designed innovations [30]. It includes a simple method for organizing data in a computerized manner on digital devices, and having accessible data increases the efficiency of many computerized operations. In regard to storing and recovering data, capacity devices may use optical, electromagnetic, or other media. Information capacity makes record recovery and reinforcement techniques essential in the event of an unforeseen computer malfunction or cyber-attack [31, 32]. Each association should consider the following factors while building this up: credibility, rationality of the stockpile design, and safety features [12].

Security [F4] The growing force that is helping security professionals and instrument vendors accomplish much more with log and event data is security big data investigation, often known as network safety examination [28]. The security used to be limited to physically characterizing connection rules, which were brittle, hard

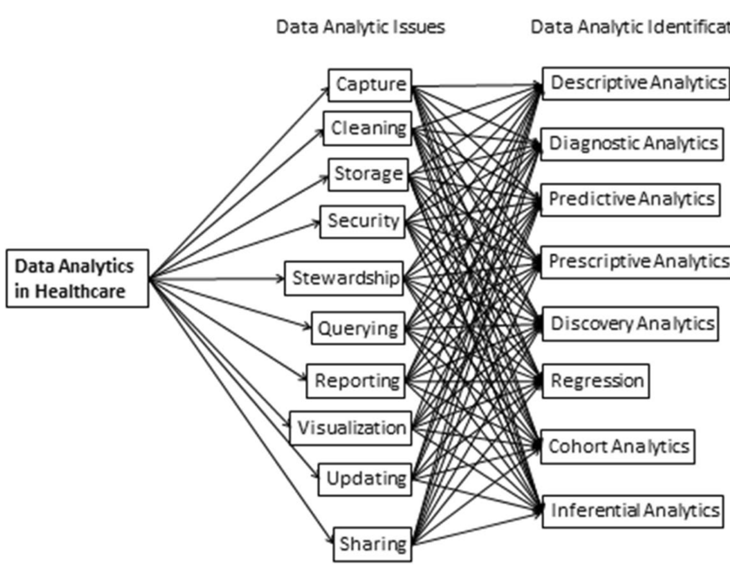

Fig. 3 Data analysis affecting factors and alternative hierarchy

to maintain, and had many false positive aspects. Security frameworks can benefit from new AI techniques that allow them to identify threats and instances with much more precision and without the need for prior definitions, rules, or attack marks [24]. That said, AI requires a large amount of data to be persuasive. The challenge is storing far more data than in the past, breaking it down as quickly as possible, and sorting out new information.

Stewardship [F5] Information stewardship is a collection of skills that ensures that an organization's information resources are accessible, useful, secure, and reliable [33]. The whole information lifecycle from production, assortment, preparation, and usage to information capacity and cancellation must be managed and directed [23]. Ensuring that clients have access to high-quality, dependable information is the responsibility of information stewardship. To ensure information quality and consistency, information stewardship adheres to an association's information management guidelines.

Querying [F6] combined data from several queries from similar or disparate information sources into a single conclusion set by using perceptive questions. To extract knowledge from a few distinctive informational configurations, some could be hidden in different information sources [34]. It can become tiresome to examine every information layout, which will ultimately lead to unnecessary time and confusion when you query the board cycle. This may combine the findings of many inquiries that span different information sources into a single query result seen by using perceptive questions [35]. A large number of questions can be added to scientific investigations in various combinations, allowing the creation of a single, comprehensive result set that includes the precise data you are looking for.

Reporting [F7] Information reporting is a scientific tool that helps organizations grow more quickly by separating past, current, and future execution experiences. It connects many data sources and is often used on a functional and essential level of autonomous guidance [2]. As previously mentioned, these reports included highlights of static displays of information that were physically assembled or determined. However, with the addition of current cycles, such as dashboard detailing, they have developed into an invaluable tool for managing your deal processes, advertising data, and surprisingly strong assembling examinations, among other authoritative cycles that are predicted to remain consistent over the competition.

Visualization [F8] the graphical representation of data and information is known as information perception. Information representation tools offer an open way to examine and identify patterns, exceptions, and instances in information by using visual elements such as outlines, diagrams, and guides. Additionally, it provides workers and businesses with a fantastic approach to convey knowledge to no specialized masses without chaos [36]. Information representation technologies and developments are essential in the field of enormous amounts of information to analyze large amounts of data and make decisions based on information.

Updating [F9] the frequency with which you should update your information examination process depends on a number of variables, including the nature of your company, the amount and velocity of your information, and the specific goals you need to achieve through research. Generally, it is advised to audit and update your system once a year to make sure it keeps up with your evolving company requirements and technological advancements [37, 38].

Sharing [F10] the process of making comparable information assets available to other applications, clients, or associations is known as information sharing [39]. It combines technological developments, practices, legal frameworks, and social features that support safe access to information for many parties without sacrificing the reliability of the information. Sharing information fosters collaboration with vendors and partners and increases efficiency within an organization. Understanding the risks and opportunities associated with sharing information is essential to the cycle [6].

Data analytic alternatives

The DA can manage information and focus data using a few scientific techniques. Different types of data analytics approaches are selected as alternatives.

The application of descriptive analytics [ALT1] factual comprehension to dissect verified data to identify patterns and relationships is known as graphic research. An illuminating analysis attempts to depict a situation, anomaly, or outcome [40]. It understands historical trends and provides organisations with a perfect foundation from which to pursue them. Unmistakable research is linked to locating critical insider knowledge. Information needs to be set: research should provide the when, where and how of the transformation, along with measurable instances. In the realm of information analysis, one of the four essential categories is engaged exploration [41]. Prescriptive investigation, prophetic examination, and demonstrative investigation are the others.

Diagnostic Analytics [ALT2], the most popular method of using data to determine the causes of patterns and relationships between components is diagnostic analysis [42]. The use of clarifying analysis to identify trends might be viewed as a logical next step [43]. It should be feasible to perform a physical examination, use a computer program, or use factual programming (such as Microsoft Excel) to examine symptoms.

Predictive analytics [ALT3] the most popular method of using knowledge to predict future outcomes is predictive inquiry [44]. The cycle looks for ideas that might predict future behavior by using quantifiable models, artificial intelligence (AI), information analysis, and human intelligence [45]. Associations may provide very accurate predictions about patterns and behaviors that will emerge in seconds, days, or years from now by using relevant and up-to-date data.

Prescriptive analytics [ALT4] makes it easier than ever to leverage collected data to produce true commercial value for organizations because of the vast amount of information that is already available to them. Nevertheless, it could be difficult to determine the best method for decomposing these data [46]. This phrase, "the fate of information investigation," accurately describes prescriptive examination. This kind of research suggests the optimal course of action moving forward, going beyond explanations and projections. It is very useful for directing information-informed behavior [47].

Discovery analytics [ALT5] an approach known as discovery analytics helps clients of all specializations identify the most pertinent information that is readily available to them to enhance their information research. It involves gathering data from a variety of sources and examining potential experiences that the data may reveal before advancing with state-of-the-art analysis techniques, such as artificial intelligence and quantifiable demonstration [41]. Information revelation is a four-step process that includes gathering data from many sources, modifying the data, performing a visual analysis, and using advanced investigative techniques [41]. It may also entail distributing the data across other partners to obtain their fresh perspectives and enable them to explore the data in search of experiences that might prompt more questions.

Regression [ALT6] relapse is a scientific approach used in finance, effective financial planning, and other fields that aims to determine the nature and strength of the relationship between a series of various factors and one ward variable [48]. Regression analysis is a valuable tool for identifying the connections between the variables seen in data, but much work is needed to prove causality [49]. It is applied in a few contexts related to finance, business, and money. It is used, for instance, to help venture leaders value their resources and understand the relationships between various components, such as the costs of products and the suppliers of companies that handle those goods.

Cohort Analytics [ALT7], a type of social analysis known as cohort analytics divides the data from a particular online business platform, web application, or online game and examines them into related groups rather than looking at all of the users as a single entity [50]. These linked groups, or partners, typically have common traits or experiences during a defined time period. A tool to measure client commitment over time is companion investigation. It helps determine whether customer loyalty is actually improving over time or is only appearing to do so as a result of advancement. Cohort analysis is crucial since it helps separate commitment and development metrics, as commitment problems may be hidden by development [51].

Inferential Analytics [ALT8] the instances derived from population data, inferential measures aid in the development of a reasonable understanding of the data. It uses many scientific instruments and tests to aid in conjecturing about the population [52]. Numerous examination techniques are used to select random instances that will accurately address the population. Simple irregular testing, demarcated examination, group inspection, and exact examination processes are some of the important tactics.

Fuzzy-AHP

The approach used for decision making is called fuzzy AHP. It is the strategy that allows for incredibly organized extents of objectives, or degrees of leadership, to analyze any perplexing issue. The problem is isolated clearly into a tree form to provide an explanation utilizing fuzzy AHP, as shown in Fig. 4, and the availability shape is displayed. This network topology is built by utilizing the perspectives of experts and the literature. Constructing the Triangular Fuzzy Number (TFN) from the hierarchical design is the corresponding step [53]. The influence of one norm on several standards may be used to help with the length evaluation of each social occasion

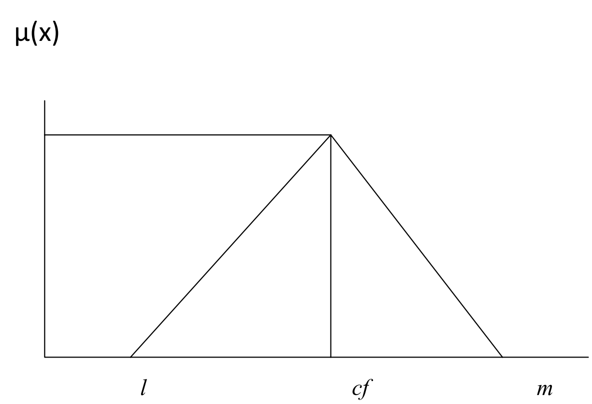

Fig. 4 TFN

of the desired aims, which is an essential task of accurate decision making in the healthcare domain.

Moving forward, etymological traits are being transformed into new numerals and TFNs. The TFN is used by the researchers in this study, and it ranges from 0 to 1. The computational simplicity of TFN enlistment limitations and their capacity to manage fuzzy data provide a rationale for this choice of TFN [54]. Moreover, phonetic components are labeled generally basic, pitifully enormous, and so on, while new qualities are assigned a number ranging from one to nine. Assuming that situations 1 and 2 see fuzzy number P on Q as having cooperation restrictions, it is referred to as TFN.

$$\mu_a(x) = a \rightarrow [0,1] \tag{1}$$

$$\mu_a(x) = \{\frac{x}{cf-l} - \frac{l}{cf-l} x \in [l, cf] \frac{x}{cf-mb} - \frac{mb}{cf-mb} x \in [cf, m] \tag{2}$$

Here, the lower limit focus furthest point and maximum limit are represented by the l, cf, and m, respectively. The research analysis framework for the selection of DA technique by the methods of fuzzy AHP and fuzzy TOPSIS is shown in Fig. 5.

The TFN is abbreviated as (l, cf, m). As shown by the scale presented in Table 1, the experts allocated impressions to the components influencing the features in a comprehensible manner.

Where i and j are the line and section of the two-layered network, respectively, and Eqs. 3, 4, 5, and 6 are taken into account while transforming the numerical features into TFNs that are allocated as $(l_{ij}, cf_{ij}, m_{ij})$, where l_{ij} is less regarded, cf_{ij} is the focus worth, and m_{ij} is the most significant level event. Furthermore, $TFN_{[ij]}$ is understood to mean:

$$\Phi_{ij} = (l_{ij}, cf_{ij}, m_{ij}) \tag{3}$$

$$where\ l_{ij} \leq cf_{ij} \leq m_{ij}$$

$$l_{ij} = cfn(J_{ijd}) \tag{4}$$

$$cf_{ij} = (J_{ij1}, J_{ij2}, J_{ij3})^{\frac{1}{x}} \tag{5}$$

$$and\ m_{ij} = max(J_{ijd}) \tag{6}$$

In Eqs. 3, 4, 5, and 6, J_{ijd} displays the near-status of the attributes between two variables that are not fully resolved by d, while i and j indicate two components that are selected by experts. For a given connection, Φ_{ij} is assessed using the geometrical mean of the expert opinions. The DA approach is ready to join and indicates the precise arrangement of experts and displays the highest and lowest scores for overall centrality between the components. The TFN values also increased under Eqs. 7, 8, and 9. Consider the following two TFNs $M1 = (l1, cf1, m1)$ and $M2 = (l2, cf2, m2)$. The fundamentals of exercise are as follows:

$$(l_1, cf_1, m_1) + (l_2, cf_2, m_2) = (l_1 + l_2, cf_1 + cf_2, m_1 + m_2) \tag{7}$$

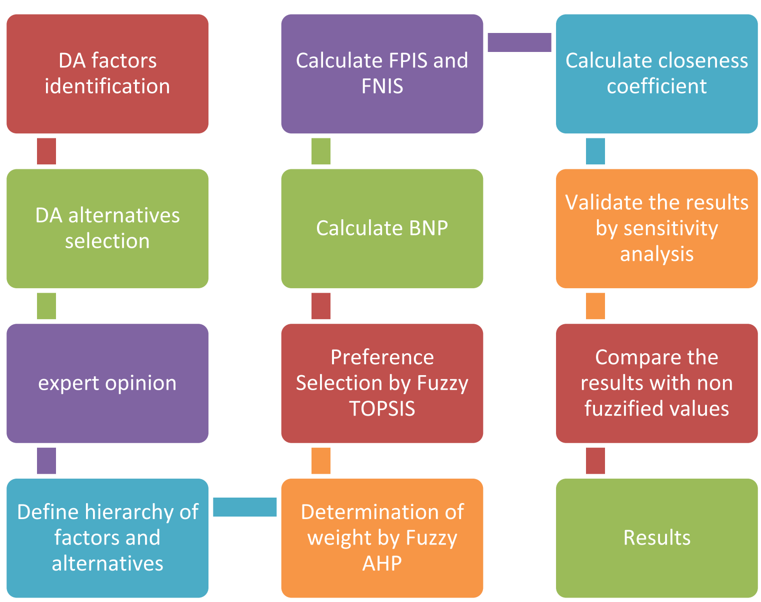

Fig. 5 Flow diagram of fuzzy AHP-TOPSIS

Table 1 TFN Scale

Pattern	Scale	TFN Value
1	Indistinguishable noteworthy	(1 1 1)
2	Irregular values between two adjacent measurements	(1 2 3)
3	Weakly noteworthy	(2 3 4)
4	Irregular values between two adjacent measurements	(3 4 5)
5	Impartially noteworthy	(4 5 6)
6	Irregular values between two adjacent measurements	(5 6 7)
7	Firmly noteworthy	(6 7 8)
8	Irregular values between two adjacent measurements	(7 8 9)
9	Definitely noteworthy	(9 9 9)

$$(l_1, cf, m_1) \times (l_2, cf_2, m_2) = (l_1 \times l_2, cf_1 \times cf_2, m_1 \times m_2) \quad (8)$$

$$(l_1, cf_1, m_1)^{-1} = \left(\frac{1}{l_1}, \frac{1}{cf_1}, \frac{1}{m_1}\right) \quad (9)$$

The Eq. 10 is used to produce a fuzzy range connection structure as a $n \times n$ cross section after obtaining the TFN for each set of evaluations.

$$\widetilde{A^d} = \left[\widetilde{k}_{11}^d \widetilde{k}_{12}^d \ldots \widetilde{k}_{1n}^d \widetilde{k}_{21}^d \widetilde{k}_{22}^d \ldots \widetilde{k}_{2n}^d \cdots\cdots\cdots \widetilde{k}_{n1}^d \widetilde{k}_{n2}^d \ldots \widetilde{k}_{nn}^d\right] \quad (10)$$

where $\widetilde{k_{ij}^k}$ speaks to the '*ith*' models' '*dth*' pioneering tendency over the '*jth*' measurements. When many DA approaches are available, Eq. 11 is used to obtain the average of each tendency.

$$\widetilde{k}_{ij} = \sum_{d=1}^{d} \widetilde{k}_{\mathrm{ij}}^{\mathrm{d}} \quad (11)$$

The next step is to resurrect the range connection systems for each approach in the chain of importance in light of Eq. 12 tracking of the center worth of trends.

$$\widetilde{A} = [\widetilde{A_{11}} \ \ldots \ \widetilde{k_{1n}} \ \cdots \ \ddots \ \cdots \ \widetilde{k_{n1}} \ \cdots \ \widetilde{k_{nn}}] \quad (12)$$

After this, we utilize the geometric mean approach as shown in Eq. 13 to depict the fuzzy geometric mean and fuzzy loads of each factor.

$$\widetilde{p}_i = \left(\prod_{j=1}^{n} \widetilde{k}_{\mathrm{ij}}\right)^{\frac{1}{n}}, i = 1,2,3\ldots n \quad (13)$$

The following stage is to finish up the fuzzy load of the factor with the assistance of Eq. 14.

$$\widetilde{w}_i = \widetilde{p}_i \otimes \left(\widetilde{p}_1 \oplus \widetilde{p}_2 \oplus \widetilde{p}_3 \ldots. \oplus \widetilde{p}_n\right)^{-1} \quad (14)$$

Furthermore, the normal and standardized weight criteria were determined with the assistance of Eqs. 15 and 16.

$$M_i = \frac{\widetilde{w}_1 \oplus \widetilde{w}_2 \ldots.. \oplus \widetilde{w}_n}{n} \quad (15)$$

$$Nr_i = \frac{M_i}{M_1 \oplus M_2 \oplus \ldots\cdots \oplus M_n} \quad (16)$$

Additionally, with the aid of condition 17, the focal point of the region system is used to calculate the best non-fuzzy execution (BNP) evaluation of the fuzzy loads on the assessment.

$$BNPwD1 = \frac{[(uw1 - lw1) + (miw1 - lw1)]}{3} + lw1 \quad (17)$$

Fuzzy TOPSIS

The fuzzy TOPSIS approach is based on probability, which has the most constrained and remote approach from the positive and negative ideal reactions for ideal and least spectacular methods, respectively [35]. Experts handle problems by communicating a certain display score to a decision regarding measurements [11]. To preserve consistency with the existing fuzzy state, TOPSIS distributes fuzzy numbers with an enhanced propensity to precise numbers, speaking to the general centrality of criteria. Using '*p*' choices as a mathematical technique, '*m*' concentrations occur inside the n-layered region of the problem; TOPSIS viewpoints handle a multi check decision, thus creating a commotion.

Furthermore, under fuzzy conditions, the hybrid approach of the fuzzy AHP and fuzzy TOPSIS techniques is often suitable for resolving acceptable decision making problems. This approach is in accordance with the attached selection of a large number of DA approaches. Equations 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15 and 16 use the fuzzy AHP to compute the DA weight in the healthcare domain. Additionally, the experts use Eq. 18 and Table 2 to guide them as they seek the fuzzy decision system and select the best semantic parts to replace the rules.

Table 2 Verbal scales

Expert Response	Corresponding (TFN) or Equivalent Numerals
Worst	(0 1 3)
Bad	(1 3 5)
Average	(3 5 7)
Good	(5 7 9)
Very Good	(7 910)

$$\widetilde{K} = \begin{array}{c} \\ A_1 \\ \ldots \\ A_m \end{array}\begin{array}{c} C_1 \; \ldots \ldots \; C_n \\ \begin{bmatrix} \widetilde{x}_{11} & \cdots & \widetilde{x}_{1n} \\ \ldots & \ddots & \ldots \\ \widetilde{x}_{m1} & \cdots & \widetilde{x}_{mn} \end{bmatrix} \end{array} \quad (18)$$

where,$\widetilde{x}_{ij} = \frac{1}{D}\left(\widetilde{x}_{ij}^{1} \cdots \oplus \widetilde{x}_{ij}^{d} \oplus \cdots \widetilde{x}_{ij}^{D}\right)$ $\widetilde{x}_{ij}^{d}$ is the *'dth'* expert's evaluation of the elective simulated intelligence with regard to factorC_j, and $\widetilde{x}_{ij}^{d}= (l_{ij}^{d}, mi_{ij}^{d}, u_{ij}^{d})$. Using Eq. 19 as support, the accompanying step aims to normalize the fuzzy decision network. The'$\widetilde{p}$' addresses the normalized fuzzy decision grid, which is represented as follows:

$$\widetilde{P} = \left[\widetilde{p}_{ij}\right]_{m \times n} \quad (19)$$

From that point on, Eq. 20 can be used to recognize the adjustment method.

$$\widetilde{p}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{mi_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}\right), \; u_j^+ = max\{u_{ij}, i = 1,2,3..n\} \quad (20)$$

However, we may set the best-needed level to be similar to 1; generally, 0 is the most obvious risk. The TFNs remain at the normalized values. The normalization method can be applied in a similar way as TFN. With the aid of Eq. 21 the weighted fuzzy normalized decision cross section ($\widetilde{Q}$) is determined.

$$\widetilde{Q} = \left[\widetilde{p}_{ij}\right]_{m \times n} i = 1,2, ..m; j = 1,2,3 \ldots n \quad (21)$$

The Fuzzy Positive-Ideal Arrangement (FPIS) and Fuzzy Negative Ideal Arrangement (FNIS) are defined as $\widetilde{q}_{ij} = \widetilde{p}_{ij} \otimes \widetilde{w}_{ij}$. The components $\widetilde{q}_{ij}$ are normalized positive TFNs, and their degrees have a location with the shut in-between time [0,, 1], according to the weighted normalized fuzzy decision cross section. Following that, we may depict the FPIS T^+ (objective levels) and FNIS R^- (the worst levels), as demonstrated in conditions 22–23.

$$T^+ = \left(\widetilde{q}_{1,\ldots\ldots}^{*}\widetilde{q}_{j,\ldots\ldots}^{*}\widetilde{q}_{n,}^{*}\right) \quad (22)$$

$$R^- = \left(\widetilde{q}_{1,\ldots\ldots}^{*}\widetilde{q}_{j,\ldots\ldots}^{*}\widetilde{q}_{n,}^{*}\right) \quad (23)$$

where $\widetilde{q}_1^* = (1,1,1) \otimes \widetilde{w}_{ij} = (Lw_j, Mw_j, Hw_j) and \widetilde{q}_{ij}^- = (0,0,0)$ and $j = 1,2,3 \ldots n$. The region compensation method may be used to assess the partitions ($\widetilde{d}_i^+$ and $\widetilde{d}_i^-$) of each and every decision from A^+ and A^- to determine the partition of every choice from FPIS and FNIS, as Eqs. 24 and 25 demonstrate.

$$\widetilde{d}_i^+ = \sum_{j=1}^{n} d\left(\widetilde{q}_{ij}, \widetilde{q}_{ij}^*\right) i = 1,2, ..m; j = 1,2,3 \ldots n \quad (24)$$

$$\widetilde{d}_i^- = \sum_{j=1}^{n} d\left(\widetilde{q}_{ij}, \widetilde{q}_{ij}^*\right) i = 1,2, ..m; j = 1,2,3 \ldots n \quad (25)$$

In the following step, closeness coefficients must be found to construct the choices that will lead to the desired levels of each variable. In light of the fuzzy proximity coefficients used to advance the choices, the closeness coefficient is used to assess the certification of the fuzzy openings [45]. Once $\widetilde{d}_i^+$ and $\widetilde{d}_i^-$ of every option have been evaluated, similarities to the ideal are not unavoidable. This movement comprehends the resemblance to a perfect plan as demonstrated by Eq. 26.

$$C\widetilde{C}_i = \frac{\widetilde{k}_i^-}{\widetilde{k}_i^+ + \widetilde{k}_i^-} = 1 - \frac{\widetilde{k}_i^+}{\widetilde{k}_i^+ + k_i^-}, i = 1,2, \ldots, m \quad (26)$$

Here, $\frac{\widetilde{k}_i^-}{\widetilde{k}_i^+ + \widetilde{k}_i^-}$ — is defined as the fuzzy fulfillment degree in the *ith* alternative, and $\frac{\widetilde{k}_i^+}{\widetilde{k}_i^+ + \widetilde{k}_i^-}$ — is characterized as the fuzzy whole degree in the *ith* alternative. In view of their positions, the choices or options are made for DA in the medical care domain.

Empirical data analysis

The Fuzzy AHP process indicates the severity of the DA problems related to the medical services sector, which are handled by F1 through F10. Figure 3 shows the assortment strategy and the sequence of DA concerns. The fuzzy TOPSIS approach provides the most insightful and optimal informational methodology. Additionally, whether this result should be used in DA for the medical services sector is investigated based on the degree of similarity. In general, DA method evaluation may be performed by abstract assessment. Quantitatively determining the optimal DA strategy in the medical service sector is challenging. One or more levels of the request's quality affect the others. It may be different. The final evaluation goal was achieved by converting the obtained qualities into chains of importance, which are depicted in Fig. 3. F1 and F10 address the DA problems to affirm the evaluation. ALT1, ALT2... ALT8 demonstrate the DA method. We evaluated the impact of DA's challenges and strategy in the field of medical care using Fuzzy AHP and Fuzzy TOPSIS, two computer-based intelligence tools. The numerical situations illustrate conditions ranging from 1 to 26. Table 1 evaluates scenarios 1 through 9 by converting the etymological traits into numerical traits and accumulating TFN values. Tables 3, 4, 5, 6, 7, and 8 shows the TFN characteristics for the length assessment network that is being created.

Table 3 Fuzzy-AHP aggregated pairwise matrix

	F1 Capture	F2 Cleaning	F3 Storage	F4 Security	F5 Stewardship	F6 Querying	F7 Reporting	F8 Visualization	F9 Updating	F10 Sharing
F1 (Capture)	(1.000, 1.000, 1.000)	(0.9000, 1.1000, 1.4000)	(1.200, 1.500, 1.700)	(0.900, 1.000, 1.100)	(2.1000, 2.9000, 3.8000)	(1.1000, 1.3000, 1.6000)	(2.1000, 2.9000, 3.8000)	(0.9000, 1.1000, 1.4000)	(1.1000, 1.6000, 1.9000)	(1.000, 1.000, 1.000)
F2 (Cleaning)	-	(1.0000, 1.0000, 1.0000)	(1.100, 1.600, 1.900)	(1.800, 1.9000, 2.1000)	(2.7000, 3.4000, 4.0000)	(2.1000, 2.7000, 3.2000)	(2.7000, 3.4000, 4.0000)	(1.0000, 1.0000, 1.0000)	(1.0000, 1.0000, 1.0000)	(0.800, 0.900, 1.100)
F3 (Storage)	-	-	(1.000, 1.0000, 1.0000)	(1.400, 1.6000, 1.9000)	(1.7000, 2.2000, 2.9000)	(1.7000, 2.1000, 2.6000)	(1.7000, 2.2000, 2.9000)	(0.5000, 0.6000, 0.9000)	(0.5000, 0.6000, 0.7000)	(1.000, 1.000, 1.000)
F4 (Security)	-	-	-	(1.000, 1.0000, 1.0000)	(1.9000, 2.5000, 2.7000)	(1.6000, 2.5000, 2.6000)	(1.9000, 2.5000, 2.7000)	(0.5000, 0.5500, 0.6000)	(0.3000, 0.5000, 0.7000)	(0.300, 0.400, 0.500)
F5 (Stewardship)	-	-	-	-	(1.0000, 1.0000, 1.0000)	(1.0000, 1.1000, 1.3000)	(1.0000, 1.0000, 1.0000)	(0.3000, 0.3500, 0.4000)	(1.0000, 1.0000, 1.0000)	(1.100, 1.600, 1.900)
F6 (Querying)	-	-	-	-	-	(1.0000, 1.0000, 1.0000)	(0.8000, 0.9000, 1.1000)	(0.3000, 0.4000, 0.5000)	(0.8000, 0.9000, 1.1000)	(1.000, 1.0000, 1.0000)
F7 (Reporting)	-	-	-	-	-	-	(1.0000, 1.0000, 1.0000)	(2.7000, 3.4000, 4.0000)	(1.0000, 1.0000, 1.0000)	(0.500, 0.600, 0.700)
F8 (Visualization)	-	-	-	-	-	-	-	(1.0000, 1.0000, 1.0000)	(0.3000, 0.4000, 0.5000)	(0.300, 0.500, 0.700)
F9 (Updating)	-	-	-	-	-	-	-	-	(1.0000, 1.0000, 1.0000)	(1.100, 1.600, 1.900)
F10 (Sharing)	-	-	-	-	-	-	-	-	-	(1.000, 1.000, 1.000)

Table 4 Weights of the DA issues

Factors	Weights	BNP	Rank
F1 **(Capture)**	(0.1500,0.1800,0.2100)	0.1600	3
F2 **(Cleaning)**	(0.1900,0.2000,0.2200)	0.1900	1
F3 **(Storage)**	(0.1300,0.1600,0.1900)	0.1500	4
F4 **(Security)**	(0.1200,0.1500,0.1800)	0.1620	2
F5 **(Stewardship)**	(0.0600,0.0800,0.1000)	0.0700	9
F6 **(Querying)**	(0.0700,0.0900,0.1300)	0.0900	6
F7 **(Reporting)**	(0.0800,0.1000,0.1300)	0.1000	5
F8 **(Visualization)**	(0.0500,0.0800,0.1200)	0.0800	8
F9 **(Updating)**	(0.0620,0.0800,0.1100)	0.0680	10
F10 **(Sharing)**	(0.0730,0.0900,0.1300)	0.0880	7

Table 3 shows the different DA parameters, F1 to F10, and their TFNs, weights and BNPs, as shown in Table 4.

The fuzzy AHP approach determines the weight of the DA issues, and cleaning has the highest weight, followed by stewardship, while sharing has the lowest weight. Table 4 shows the quantitative values of the estimation, and Fig. 6 shows the corresponding graphical values.

The Tables 5, 6, and 7 provide the assessed values of subjective cognition from Eq. 20. An analysis of the normalized fuzzy decision matrix is given by Eq. 18. The values of the weighted normalized decision matrix are obtained from Eqs. 24 and 25. These values are considered using the fuzzy TOPSIS approach.

The Table 8 is evaluating for determine the degree of closeness through Eq. 26. The fuzzy TOPSIS and the degree of closeness of different DA alternatives in the healthcare sector are shown in Fig. 7. The DA results from F1 to F10 and their deterministic approach (ALT1 to ALT8) in the healthcare sector are satisfactory due to the use of expert opinion and questionnaire data. Furthermore, we have mentioned the degree of closeness in a bar chart, as shown in Fig. 7.

Comparisons

The Fuzzy AHP and Fuzzy TOPSIS strategies are used to assess the effectiveness and precision of the outcome obtained [55]. In AHP and TOPSIS, the technique of information accumulation and assessment is equivalent to that in fuzzy AHP and fuzzy TOPSIS, yet no fuzzifications are utilized [11]. In this manner, values are taken in their real number design for a regular AHP-TOPSIS. Table 9 displays the differences between the final results of fuzzy and regular AHP-TOPSIS techniques. Additionally Fig. 8, The Pearson relationship coefficient (PRC: 0.999167) between the results obtained with the fuzzy AHP and fuzzy TOPSIS techniques and the results driven by the traditional AHP-TOPSIS approach is remarkably high. In comparison to the conventional AHP TOPSIS strategy, fuzzy TOPSIS and fuzzy AHP are enhanced techniques that offer more consistency and viability. Figure 8 show a reference graphic showing the comparison of techniques.

Sensitivity analysis

Sensitivity analysis was used to validate the results for each factor of DA and its impact on the DA alternative. This is shown in Table 10. The weight of the DA components determines the responsiveness assessment. The DA alternatives are verified in our analysis through many iterations of every component, each of which is analyzed differently to reveal a range of results, as shown in Table 10. The closeness coefficient (CC) is computed using the fuzzy AHP and TOPSIS. The system is based on the weight of each variable (F1 to F10 are considered consistent). In Table 10, initial weights are displayed in the principal row; factors F1 to F10 have a high fulfillment degree CC based on unique results. Ten experiments, namely, experiments exp-0 to exp-10, are evaluated, and the alternatives from ALT1 to ALT8 (shown in Fig. 9) are evaluated. According to the obtained findings, in every test, option ALT2 had the least burden. The graphical representation is shown in Fig. 9.

Results

Our findings also demonstrate the unique aspects of DA in the healthcare sector and its connection to competent DA techniques and DA factor assessment. The fuzzy AHP and TOPSIS techniques were fully employed in the investigation. This is because the AHP approach differs in that it makes use of an AHP rather than a tree structure. The DA scientist then recalled plan tactics as a component of the order's underlying stage in the momentum investigation, which had a substantial impact on the outcomes. There is no synchronous approach for evaluating the DA technique in the healthcare sector. The main goal of this research is to assess how the data analysis approach is employed for the determination of data in the healthcare domain and its impact on different DA techniques. This analysis aims to assist healthcare professionals, data scientists, and developers in determining which DA technique makes the most sense for logical advancements in the DA in the healthcare sector. The reluctant Fuzzy AHP and TOPSIS technique was used in combination with the multi standard navigation framework to examine the effects of several DA factors. DA factors and techniques are important in the healthcare industry.

Compared to the other DA factors, F2 (cleaning) > F4 (security) > F1 (capture) > F3 (storage) > F7 (reporting) > F6

Table 5 Subjective cognition results

Factors/ Alternatives	F1 (Capture)	F2 (Cleaning)	F3 (Storage)	F4 (Security)	F5 (Stewardship)	F6 (Querying)	F7 (Reporting)	F8 (Visualization)	F9 (Updating)	F10 (Sharing)
ALT1 (Descriptive Analytics)	(5.0000 7.0000 8.9000)	(4.4000 6.4000 8.4000)	(4.4000 6.4000 8.3000)	(2.6000 4.6000 6.6000)	(4.4000 6.4000 8.4000)	(4.4000 6.4000 8.3000)	(2.6000 4.6000 6.6000)	(4.4000 6.4000 8.4000)	(4.4000, 6.4000, 8.3000)	(2.6000, 4.6000, 6.6000)
ALT2 (Diagnostic Analytics)	(5.2000 7.2000 9.0000)	(4.6000 6.6000 8.6000)	(3.8000 5.8000 7.7000)	(2.6000 4.6000 6.6000)	(4.6000 6.6000 8.6000)	(3.8000 5.8000 7.7000)	(2.6000 4.6000 6.6000)	(4.6000, 6.6000, 8.6000)	(3.8000, 5.8000, 7.7000)	(2.6000, 4.6000, 6.6000)
ALT3 (Predictive Analytics)	(4.6000 6.6000 8.6000)	(3.6000, 5.6000, 7.6000)	(4.0000 6.0000 7.9000)	(3.0000 5.0000 7.0000)	(3.6000 5.6000 7.6000)	(4.0000 6.0000 7.9000)	(3.0000 5.0000 7.0000)	(3.6000, 5.6000, 7.6000)	(4.0000, 6.0000, 7.9000)	(3.0000, 5.0000, 7.0000)
ALT4 (Prescriptive Analytics)	(5.6000 7.6000 9.2000)	(4.8000, 6.8000, 8.7000)	(4.6000 6.6000 8.4000)	(3.2000 5.2000 7.2000)	(4.8000 6.8000 8.7000)	(4.6000 6.6000 8.4000)	(3.2000 5.2000 7.2000)	(4.8000, 6.8000, 8.7000)	(4.6000, 6.6000, 8.4000)	(3.2000, 5.2000, 7.2000)
ALT5 (Discovery Analytics)	(4.8000 6.8000 8.7000)	(4.0000, 6.0000, 8.0000)	(3.8000 5.8000 7.8000)	(2.6000 4.6000 6.6000)	(4.0000 6.0000 8.0000)	(3.8000 5.8000 7.8000)	(2.6000 4.6000 6.6000)	(4.0000, 6.0000, 8.0000)	(3.8000, 5.8000, 7.8000)	(2.6000, 4.6000, 6.6000)
ALT6 (Regression)	(5.0000 7.0000 9.0000)	(4.4000, 6.4000, 8.4000)	(4.2000 6.2000 8.1000)	(2.5000 4.4000 6.4000)	(4.4000 6.4000 8.4000)	(4.2000 6.2000 8.1000)	(2.5000 4.4000 6.4000)	(4.4000, 6.4000, 8.4000)	(4.2000, 6.2000, 8.1000)	(2.5000, 4.4000, 6.4000)
ALT7 (Cohort Analytics)	(4.6000 6.6000 8.6000)	(3.6000, 5.6000, 7.6000)	(4.0000 6.0000 7.9000)	(3.0000 5.0000 7.0000)	(3.6000 5.6000 7.6000)	(4.0000 6.0000 7.9000)	(3.0000 5.0000 7.0000)	(3.6000, 5.6000, 7.6000)	(4.0000, 6.0000, 7.9000)	(3.0000, 5.0000, 7.0000)
ALT8 (Inferential Analytics)	(5.6000 7.6000 9.2000)	(4.8000, 6.8000, 8.7000)	(4.6000 6.6000 8.4000)	(3.2000 5.2000 7.2000)	(4.8000 6.8000 8.7000)	(4.6000 6.6000 8.4000)	(3.2000 5.2000 7.2000)	(4.8000, 6.8000, 8.7000)	(4.6000, 6.6000, 8.4000)	(3.2000, 5.2000, 7.2000)

Table 6 Normalized fuzzy-decision matrix

Factors/ Alternatives	F1 (Capture)	F2 (Cleaning)	F3 (Storage)	F4 (Security)	F5 (Stewardship)	F6 (Querying)	F7 (Reporting)	F8 (Visualization)	F9 (Updating)	F10 (Sharing)
ALT1 (Descriptive Analytics)	(0.5000, 0.8000, 1.0000)	(0.4800, 0.7000, 0.9000)	(0.4800, 0.7000, 0.9000)	(0.2800, 0.5000, 0.7000)	(0.4800, 0.7000, 0.9000)	(0.4800, 0.7000, 0.9000)	(0.2800, 0.5000, 0.7000)	(0.4800, 0.7000, 0.9000)	(0.4800, 0.7000, 0.9000)	(0.2800, 0.5000, 0.7000)
ALT2 (Diagnostic Analytics)	(0.6000, 0.8000, 1.0000)	(0.5000, 0.7000, 0.9000)	(0.4100, 0.6000, 0.8400)	(0.2800, 0.5000, 0.7200)	(0.5000, 0.7200, 0.9400)	(0.4000, 0.6000, 0.8400)	(0.2800, 0.5000, 0.7200)	(0.5000, 0.7200, 0.9400)	(0.4100, 0.6300, 0.8400)	(0.2800, 0.5000, 0.7000)
ALT3 (Predictive Analytics)	(0.5000, 0.7000, 0.9000)	(0.3900, 0.6000, 0.8000)	(0.4000, 0.6500, 0.8600)	(0.3300, 0.5400, 0.7600)	(0.3900, 0.6000, 0.8300)	(0.4400, 0.6500, 0.8600)	(0.3300, 0.5400, 0.7600)	(0.3900, 0.6100, 0.8300)	(0.4400, 0.6500, 0.8600)	(0.3000, 0.5000, 0.7600)
ALT4 (Prescriptive Analytics)	(0.6000, 0.8000, 1.0000)	(0.5000, 0.7000, 0.9500)	(0.5000, 0.7200, 0.9000)	(0.3500, 0.5700, 0.7800)	(0.5200, 0.7400, 0.9500)	(0.5000, 0.7200, 0.9100)	(0.3500, 0.5700, 0.7800)	(0.5200, 0.7400, 0.9500)	(0.5000, 0.7200, 0.9100)	(0.3500, 0.5700, 0.7800)
ALT5 (Discovery Analytics)	(0.5000, 0.7000, 1.0000)	(0.4000, 0.6500, 0.8700)	(0.4000, 0.6000, 0.8500)	(0.2800, 0.5000, 0.7200)	(0.4400, 0.6500, 0.8700)	(0.4100, 0.6300, 0.8500)	(0.2800, 0.5000, 0.7200)	(0.4400, 0.6500, 0.8700)	(0.4100, 0.6300, 0.8500)	(0.2800, 0.5000, 0.7000)
ALT6 (Regression)	(0.5000, 0.8000, 1.0000)	(0.4800, 0.7000, 0.9000)	(0.4600, 0.6700, 0.8800)	(0.2700, 0.4800, 0.7000)	(0.4800, 0.7000, 0.9100)	(0.4600, 0.6700, 0.8800)	(0.2700, 0.4800, 0.7000)	(0.4800, 0.7000, 0.9100)	(0.4600, 0.6700, 0.8800)	(0.2700, 0.4800, 0.7000)
ALT7 (Cohort Analytics)	(0.5000, 0.7000, 0.9000)	(0.3900, 0.6000, 0.8300)	(0.4000, 0.6500, 0.8600)	(0.3300, 0.5400, 0.7600)	(0.3900, 0.6100, 0.8300)	(0.4400, 0.6500, 0.8600)	(0.3300, 0.5400, 0.7600)	(0.3900, 0.6100, 0.8300)	(0.4400, 0.6500, 0.8600)	(0.3000, 0.5400, 0.7600)
ALT8 (Inferential Analytics)	(0.6000, 0.8000, 1.0000)	(0.5000, 0.7000, 0.9500)	(0.5000, 0.7000, 0.9100)	(0.3500, 0.5700, 0.7800)	(0.5200, 0.7400, 0.9500)	(0.5000, 0.7200, 0.9100)	(0.3500, 0.5700, 0.7800)	(0.5200, 0.7400, 0.9500)	(0.5000, 0.7200, 0.9100)	(0.3500, 0.5700, 0.7800)

Table 7 Weighted normalized fuzzy decision matrix

Factors/ Alternatives	F1 (Capture)	F2 (Cleaning)	F3 (Storage)	F4 (Security)	F5 (Stewardship)	F6 (Querying)	F7 (Reporting)	F8 (Visualization)	F9 (Updating)	F10 (Sharing)
ALT1 (Descriptive Analytics)	(0.0800, 0.1600, 0.2800)	(0.0700, 0.1500, 0.2600)	(0.0700, 0.1500, 0.2600)	(0.0400, 0.1000, 0.2100)	(0.0700, 0.1500, 0.2600)	(0.0700, 0.1500, 0.2600)	(0.0400, 0.1000, 0.2100)	(0.0700, 0.1500, 0.2600)	(0.0700, 0.1500, 0.2600)	(0.0400, 0.1000, 0.2100)
ALT2 (Diagnostic Analytics)	(0.1100, 0.2000, 0.3500)	(0.0900, 0.1900, 0.3400)	(0.0800, 0.1600, 0.3000)	(0.0500, 0.1300, 0.2600)	(0.0900, 0.1900, 0.3400)	(0.0800, 0.1600, 0.3000)	(0.0500, 0.1300, 0.2600)	(0.0900, 0.1900, 0.3400)	(0.0800, 0.1600, 0.3000)	(0.0500, 0.1300, 0.2600)
ALT3 (Predictive Analytics)	(0.0700, 0.1300, 0.2500)	(0.0500, 0.1100, 0.2200)	(0.0600, 0.1200, 0.2300)	(0.0400, 0.1000, 0.2100)	(0.0500, 0.1100, 0.2200)	(0.0600, 0.1200, 0.2300)	(0.0400, 0.1000, 0.2100)	(0.0500, 0.1100, 0.2200)	(0.0600, 0.1200, 0.2300)	(0.0400, 0.1000, 0.2100)
ALT4 (Prescriptive Analytics)	(0.0800, 0.1400, 0.2300)	(0.0700, 0.1300, 0.2200)	(0.0600, 0.1200, 0.2100)	(0.0400, 0.1000, 0.1800)	(0.0700, 0.1300, 0.2200)	(0.0600, 0.1200, 0.2100)	(0.0400, 0.1000, 0.1800)	(0.0700, 0.1300, 0.2200)	(0.0600, 0.1200, 0.2100)	(0.0400, 0.1000, 0.1800)
ALT5 (Discovery Analytics)	(0.0300, 0.0600, 0.1100)	(0.0300, 0.0500, 0.1000)	(0.0200, 0.0500, 0.1000)	(0.0200, 0.0400, 0.0900)	(0.0300, 0.0500, 0.1000)	(0.0200, 0.0500, 0.1000)	(0.0200, 0.0400, 0.0900)	(0.0300, 0.0500, 0.1000)	(0.0200, 0.0500, 0.1000)	(0.0200, 0.0400, 0.0900)
ALT6 (Regression)	(0.0400, 0.0700, 0.1300)	(0.0300, 0.0700, 0.1200)	(0.0300, 0.0600, 0.1200)	(0.0200, 0.0500, 0.0900)	(0.0300, 0.0700, 0.1200)	(0.0300, 0.0600, 0.1200)	(0.0200, 0.0500, 0.0900)	(0.0300, 0.0700, 0.1200)	(0.0300, 0.0600, 0.1200)	(0.0200, 0.0500, 0.0900)
ALT7 (Cohort Analyt- ics)	(0.0700, 0.1300, 0.2500)	(0.0500, 0.1100, 0.2200)	(0.0600, 0.1200, 0.2300)	(0.0400, 0.1000, 0.2100)	(0.0500, 0.1100, 0.2200)	(0.0600, 0.1200, 0.2300)	(0.0400, 0.1000, 0.2100)	(0.0500, 0.1100, 0.2200)	(0.0600, 0.1200, 0.2300)	(0.0400, 0.1000, 0.2100)
ALT8 (Inferential Analytics)	(0.0800, 0.1400, 0.2300)	(0.0700, 0.1300, 0.2200)	(0.0600, 0.1200, 0.2100)	(0.0400, 0.1000, 0.1800)	(0.0700, 0.1300, 0.2200)	(0.0600, 0.1200, 0.2100)	(0.0400, 0.1000, 0.1800)	(0.0700, 0.1300, 0.2200)	(0.0600, 0.1200, 0.2100)	(0.0400, 0.1000, 0.1800)

Table 8 Closeness coefficients to the desired level among different alternatives

Alternatives	dþi	Di	Gaps CCþi	CCi
ALT1 (Descriptive Analytics)	0.23000	0.49000	0.67000	0.33120
ALT2 (Diagnostic Analytics)	0.81000	0.93000	0.78000	0.22240
ALT3 (Predictive Analytics)	0.26000	0.51000	0.65000	0.35250
ALT4 (Prescriptive Analytics)	0.33000	0.48000	0.64000	0.40550
ALT5 (Discovery Analytics)	0.44000	0.61000	0.59000	0.41470
ALT6 (Regression)	0.28000	0.32000	0.52000	0.48490
ALT7 (Cohort Analytics)	0.31000	0.42000	0.58000	0.42560
ALT8 (Inferential Analytics)	0.43000	0.53000	0.55000	0.45510

(querying) > F10 (sharing) > F8 (visualization) > F5 (stewardship) > F9 (updating). Security is the top priority for cleaning DAs, and developers, scientists and doctors must be sure to consider this issue during investigations. Updating the DA was given the lowest priority in the healthcare sector. The alternative DA rankings were evaluated by the fuzzy TOPSIS technique: ALT6 (regression) > ALT8 (inferential analytics) > ALT7 (cohort analytics) > ALT5 (discovery analytics) > ALT4 (prescriptive analytics) > ALT3 (predictive analytics) > ALT1 (descriptive analytics) > ALT2 (diagnostic analytics). The regression technique of the data analysis alternative was the most common, followed by inferential analysis in this analysis with the selected factors of DA.

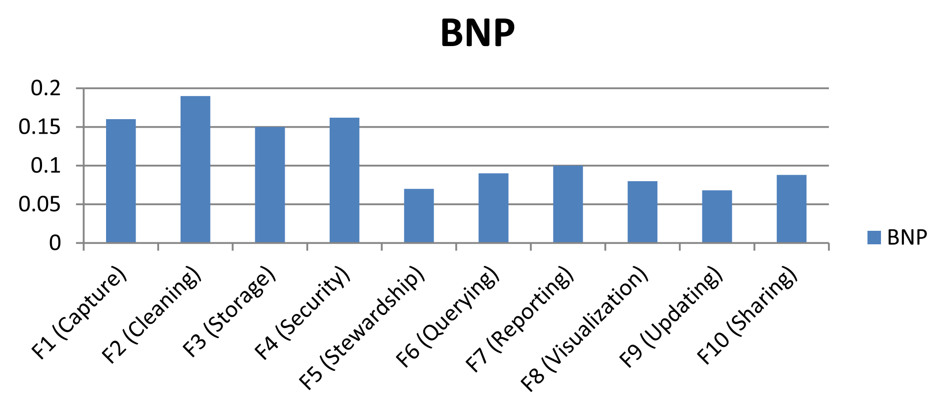

Fig. 6 Graphical representation of the weights of the DA issues

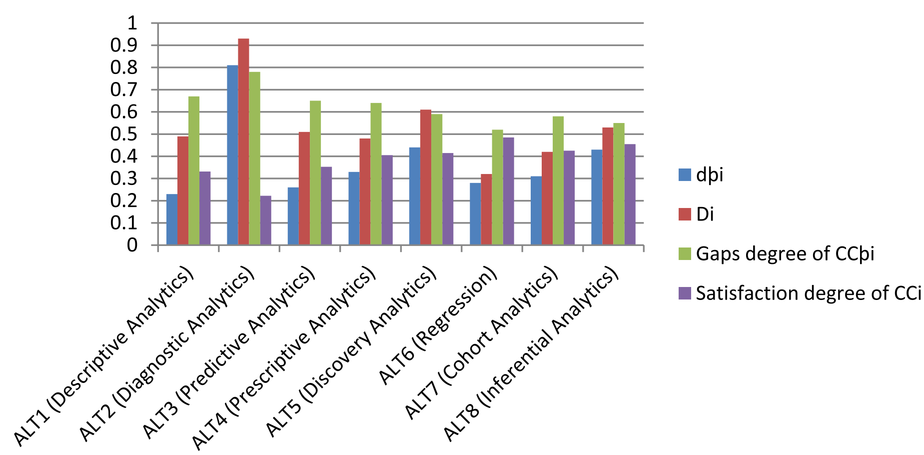

Fig. 7 Graph of the degree of satisfaction

Table 9 Comparison between AHP TOPSIS and Fuzzy-AHP-TOPSIS

Methods/Alternatives	ALT1	ALT2	ALT3	ALT4	ALT5	ALT6	ALT7	ALT8
Fuzzy-AHP-TOPSIS	0.3412	0.2324	0.3425	0.3955	0.4047	0.4749	0.4156	0.4651
Classical-AHP-TOPSIS	0.3356	0.2326	0.3461	0.3958	0.4056	0.4758	0.4198	0.4560

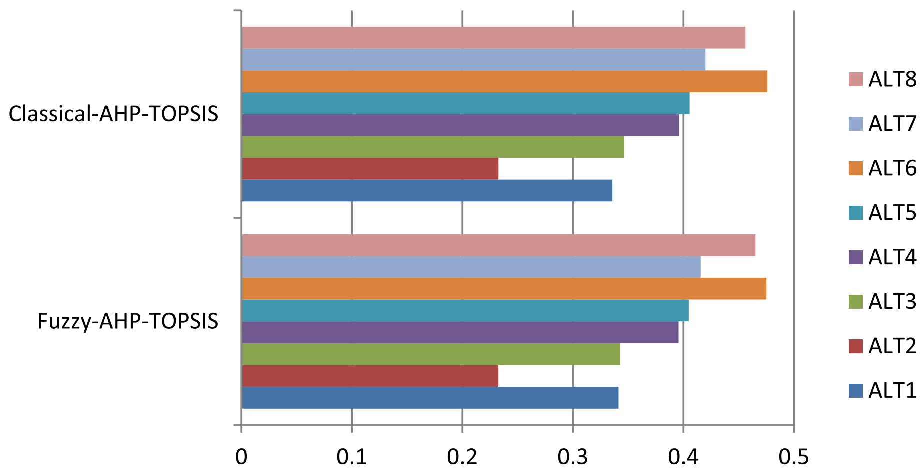

Fig. 8 Bar graph of the results of AHP TOPSIS and fuzzy AHP-TOPSIS

Table 10 Sensitivity analysis

Experiments	Weights/Alternatives		ALT1	ALT2	ALT3	ALT4	ALT5	ALT6	ALT7	ALT8
Experiment 0	Original Weights	Satisfaction Degree (CC-i)	0.3412	0.2324	0.3625	0.4155	0.4247	0.4949	0.4356	0.4651
Experiment 1	F1		0.3623	0.2475	0.3771	0.4313	0.4306	0.5063	0.44179	0.4881
Experiment 2	F2		0.3113	0.2375	0.3641	0.4198	0.4211	0.5058	0.4368	0.4715
Experiment 3	F3		0.3436	0.2332	0.3711	0.4138	0.4166	0.5043	0.4338	0.4667
Experiment 4	F4		0.3526	0.0545	0.3585	0.4039	0.4258	0.4953	0.4371	0.4762
Experiment 5	F5		0.3138	0.1999	0.3253	0.3886	0.3842	0.4665	0.4021	0.4346
Experiment 6	F6		0.2665	0.1509	0.2805	0.3453	0.3378	0.4228	0.4148	0.3882
Experiment 7	F7		0.3583	0.2378	0.3703	0.4382	0.4226	0.5115	0.4448	0.4764
Experiment 8	F8		0.3429	0.2495	0.3681	0.4238	0.4329	0.4964	0.4388	0.4833
Experiment 9	F9		0.3138	0.1999	0.3253	0.3886	0.3842	0.4665	0.4021	0.4346
Experiment 10	F10		0.2665	0.1509	0.2805	0.3453	0.3378	0.4228	0.4148	0.3882

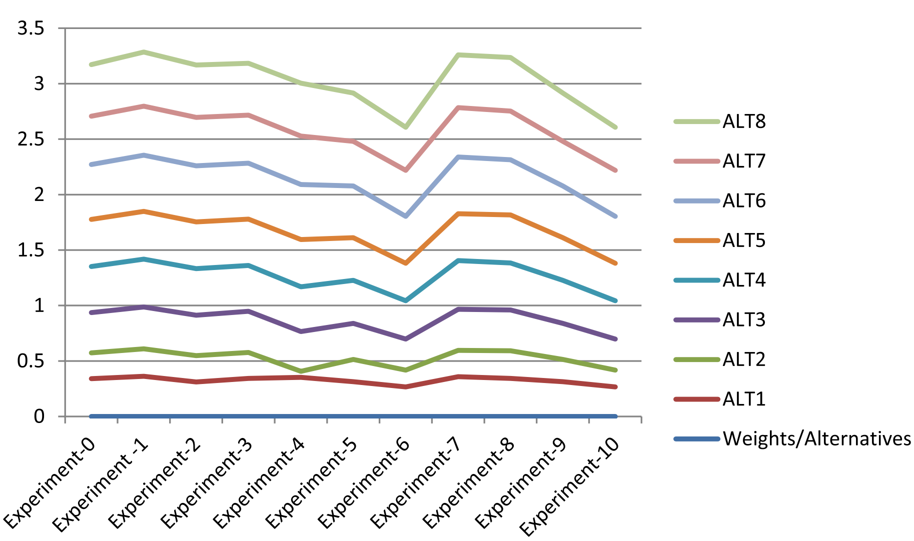

Fig. 9 Sensitivity analysis

The DA approach of diagnostic analytics achieved the lowest rank in the quantitative assessment. Evaluating how DA innovation structures affect the healthcare sector not only identifies a feature of the technology but also provides guidance to engineers. This investigation aids DA scientists in selecting and prioritizing essential DA innovation components for reliable and secure DA in healthcare applications.

This study provides a thorough evaluation of several strategies to improve DA in the healthcare sector. Even though its applicability may be limited, this assessment may be significant to DA scientists given the complexity of DA in an innovative environment. DA experts face a plethora of new challenges on a regular basis. There may be more sensible multi standard navigation balanced advancements for catering to multi standard navigation issues, even though the combination of the fuzzy AHP and TOPSIS approaches for evaluating the impact of DA innovation on the healthcare sector is effective and significant. The authors focused their response and analysis research on the results to be used as a future reference.

Conclusions

This research analysis is based on the selection of DA technique in healthcare sector, uses an integrated fuzzy AHP technique to statistically evaluate several DA dependent factors and produces the weight of the factors; data cleaning got the highest weight and data updating least. The results of this study offer significant insights for experts involved in the selection of DA technique in healthcare sector. These findings can be utilized to provide guidance for improvement and to assist specialists in refining their DA techniques. However, it is crucial to understand the unique limitations of this study that should be taken into account in further evaluations. One limitation pertains to the collection of data on DA. Such data are crucial for progress, and their extensive nature can make it challenging to comprehend and analyze fully. Despite these limitations, the findings of this study still hold value and can contribute to the advancement of DA. Future assessments can address the data challenge by employing more efficient data collection methods, employing advanced analytical techniques, or focusing on specific subsets of data that are most relevant to the research objectives. By acknowledging and addressing these limitations, future studies can build upon the current findings and provide further insights into the development of DA technique. Improvement guidelines may be provided for this evaluation to aid professionals in refocusing the forward motion of advancement. There may be a few limitations to this assessment that should be kept in mind for further evaluations. The limitations of the results are as follows:

- Progress depends on the information collected through the specialist. It could be difficult to comprehend how much of the information is given to the outcomes.
- This review may have missed several more practical, manageable dependent factors of DA.

The results analyzed in this paper show how DA factors impact the healthcare sector and provide the most suitable DA techniques. This study provides the best DA approach for practitioner by simulating the results and providing insights into different DA techniques and their effects for the future. Additionally, to enhance the accuracy of the results for later use, the authors conducted awareness and analysis studies.

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

AA, MN, and MAS wrote the initial draft of the paper. MN collects the data for the analysis. WA, HA, and BA evaluate the data analysis and revise the manuscript. MN and AhA assesses the data from the different sources. RA was supervised the project.

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Availability of data and materials

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interest.

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