Aljohani
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RESEARCH

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AI-Driven decision-making for personalized elderly care: a fuzzy MCDM-based framework for enhancing treatment recommendations

Abeer Aljohani[1*]

Abstract

Background Global healthcare systems face enormous challenges due to the ageing population, demanding novel measures to assure long-term efficacy and viability. The expanding senior population, which requires specialised and efficient healthcare solutions, emphasises the importance of improving healthcare sustainability. Recognising the importance of personalised healthcare recommendations in improving patient outcomes as well as facility sustainability, this study tackles the crucial need for targeted treatments to help the elderly navigate the complicated healthcare landscape.

Objectives Through the integration of automation with the Fuzzy VIKOR approach as well as Electronic Health Record (EHR) data, this work seeks to create an automated decision-making mechanism that improves personalised healthcare suggestions for the elderly. By using automated data-driven observations, Fuzzy VIKOR to handle decision-making uncertainty as well as the clinical depth of EHR data, the primary objective is to increase the efficacy and accuracy of treatment choices. In order to guarantee that treatment recommendations are not only medically beneficial but also in line with each patient's needs and preferences, this research aims to close the gap between automated intelligence as well as patient-centered care.

Method The Fuzzy VIKOR approach is used with Electronic Health Record (EHR) data to establish a strong framework for personalised healthcare recommendations. AI techniques are employed to enhance data processing, while Fuzzy VIKOR is used to control uncertainty in decision-making, whereas EHR data gives comprehensive clinical insights. The combination of these aspects enables the creation of a system that compensates for uncertainties in medical knowledge and patient preferences, culminating in a ranked array of treatment alternatives customised to the difficulties of healthcare decision-making for the aged.

Results The study shows how the proposed methodology improves therapy selection for senior populations. By combining AI-powered analysis, Fuzzy VIKOR, and EHR data, the study provides a refined and personalised approach to healthcare recommendations, providing ranked treatment alternatives based on individual characteristics and preferences. The findings demonstrate the potential of this strategy to handle healthcare complexity and contribute to the developing era of precision medicine.

Conclusion Finally this study makes an important contribution to the continuing discussion about the sustainability of healthcare for the elderly. The combination of AI-driven methodologies, the Fuzzy VIKOR technique and EHR data offers a promising approach to improving therapy selection in the setting of precision medicine. By accepting

*Correspondence:
Abeer Aljohani
aahjohani@taibahu.edu.sa

personalised healthcare recommendations, this study anticipates a future in which elderly people's unique characteristics and preferences are central to decision-making processes, maintaining not only better patient outcomes but also the long-term viability and sustainability of healthcare services for the elderly.

Keywords Artificial Intelligence, Personalized healthcare, Elder care, Treatment recommendations, Patient outcomes, Precision medicine

Background

The need to improve the sustainability of healthcare for older populations arises from the world's extraordinary demographic shift towards an ageing society. There is an increased need for healthcare services that are specifically designed to handle the special requirements and challenges connected with ageing as the number of senior people rises. Healthcare systems worldwide are under immense pressure due to the changing demographics, necessitating innovative strategies to ensure that quality care for the elderly remains both accessible and cost-effective. By placing a high priority on improving the sustainability of healthcare for this population, we not only support the well-being and longevity of the elderly but also strengthen the overall robustness and effectiveness of healthcare systems in the face of changing healthcare demands and demographic shifts. In order to fulfil the unique healthcare needs of elderly populations and create a sustainable healthcare future, it is vital that proactive steps be taken to optimise healthcare delivery, resource allocation, as well as policy frameworks.

In today's worldwide healthcare setting, a number of new initiatives are redefining how healthcare is handled and delivered. The emergent use of telemedicine as well as distant healthcare facilities is one prominent trend, spurred by advances in digital technology and the demand for accessible treatment, especially in underprivileged areas. Through the use of virtual meetings, remote surveillance of chronic illnesses, and quick access to health information, this initiative has completely changed how patients and doctors communicate [1–3]. Precision medicine has also become more popular, utilising genomics and personalised data to customise medical treatments to a person's particular genetic make-up and features. This method is changing how illnesses are identified and treated, maybe resulting in solutions that are more successful and have fewer negative effects. Electronic Health Records (EHR) are more prevalent, contributing to the worldwide push towards healthcare modernization. These digital records simplify the exchange of patient information amongst healthcare professionals, improving care coordination and minimising test duplication. Also, massive datasets are being analysed using artificial intelligence as well as machine learning to draw conclusions that help with early disease identification, treatment prediction, and medication discovery. Additionally, it is clear that a greater emphasis is being placed on wellness programmes and preventative treatment as healthcare systems realise the advantages of taking proactive steps to lower illness prevalence and medical expenses. To encourage healthier communities, behavioural changes, immunisation campaigns, as well as health education are gaining popularity. The overall objective of these newly developing healthcare efforts is to enhance healthcare outcomes, accessibility, and effectiveness on a worldwide scale [4–9]. They demonstrate a radical change towards patient-centric, data-driven, and technologically enabled approaches.

The paradigm of healthcare has changed recently in favour of a more patient-centric strategy, emphasising the significance of customising medical interventions to specific patient features. Due to their potential to considerably advance patient results while also maximising the use of healthcare resources, personalised therapy suggestions have drawn a lot of interest in this context. This newly developed method acknowledges the variety of patient profiles, taking into account everything from personal preferences to medical histories as well as genetic predispositions [10–12]. By using this extensive patient data, healthcare professionals may make better decisions, resulting in treatments that are not only more successful but also use less resources and less money than they need to. Figure 1 shows the graphical illustration of right medication with personalized healthcare treatment.

The idea of "hyper-personalized medicine" refers to the design of therapies that go beyond simple diagnosis to each patient. This strategy is gaining popularity as a result of things including increased chronic disease rates, technology improvements, growing desire for personalized therapies, and backing from regulatory agencies and healthcare systems [13–15]. The fact that there isn't much patient data available is a significant disadvantage. Complete patient data, including genetics, medical history, variables related to lifestyle as well as information, is essential for the success of hyper-personalized treatment. Data scarcity is a problem, potentially preventing advancement and the provision of focused treatments, especially for rare conditions. This restriction may impede market revenue growth over the anticipated time frame. Benefits of hyper-personalized medicine

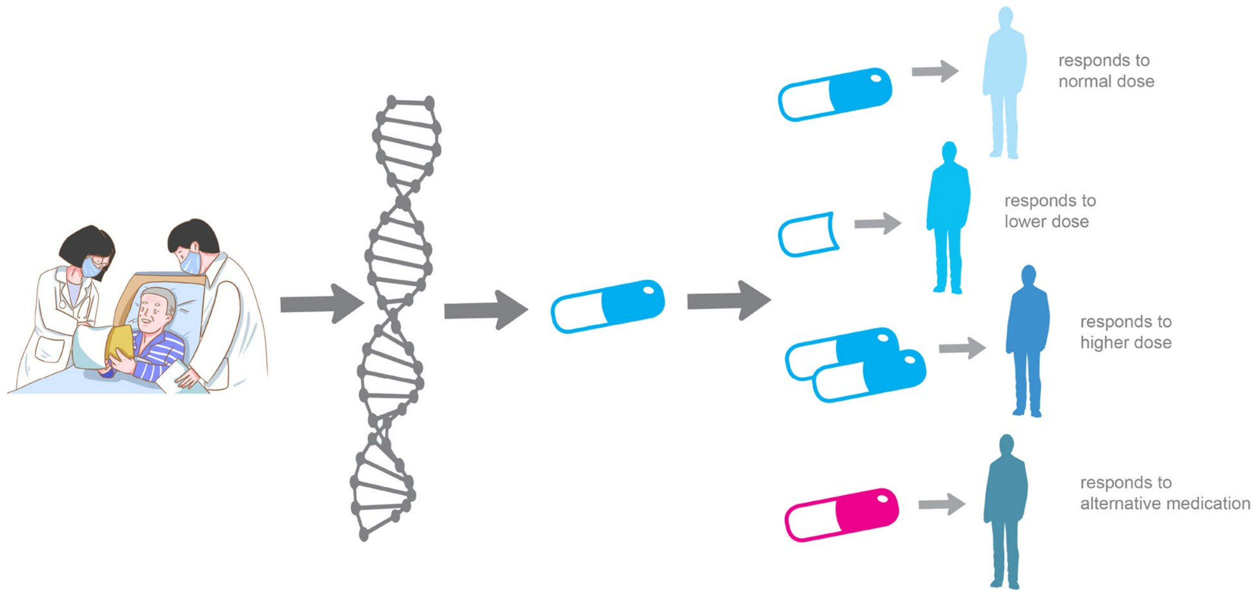

Fig 1 Right medication with personalized healthcare treatment

include improving clinical trials for pharmaceutical companies and creating more potent medications for particular patient populations. This strategy expedites medication development while reducing the likelihood of drug failure. Adverse drug reactions could be reduced by attending to the specific needs of each patient, improving patient safety and lowering healthcare expenditures. Additionally, hyper-personalized medicine spurs the development of novel treatments, creating expansion potential for industry participants.

In 2021, the market for hyper-personalized medicine was dominated by North America. The sizeable patient base in the area generates a healthy market for personalised medicine goods and services. Chronic illnesses including cancer, diabetes, as well as cardiovascular conditions are becoming more prevalent, which is driving need for highly individualised treatments that can cater to individual patient needs. The worldwide market for hyper-personalized medicine was projected to reach $2,100 billion in 2021. According to projections, this industry will grow at a compound annual growth rate (CAGR) of 11.7%, bringing in an estimated $5,886.50 billion in sales by the year 2031. The results of a market analysis of hyper-personalized medications worldwide are displayed in Figure 2 [15].

Personalised therapy recommendations have great potential, however it is challenging to transform this idea into real-world clinical applications. Electronic Health

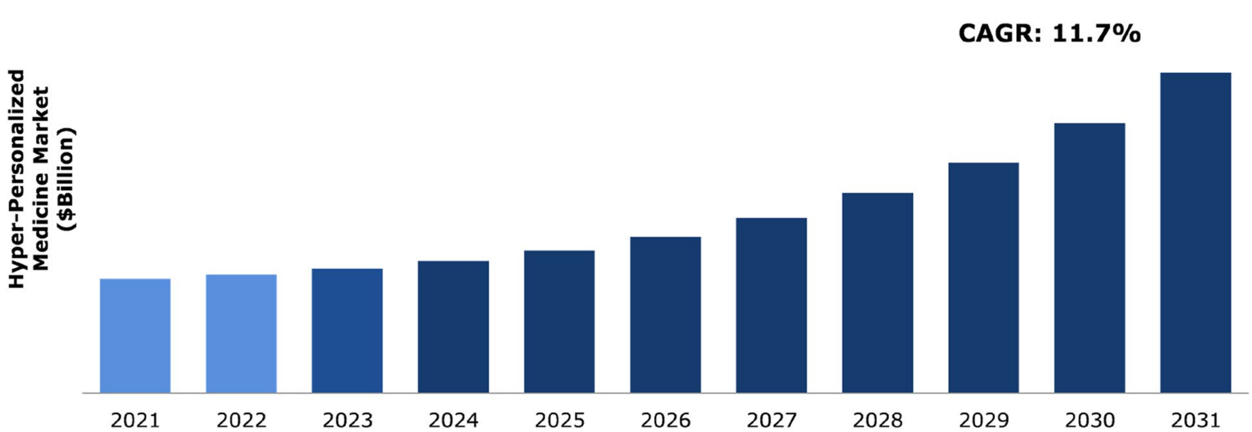

Fig 2 Global Hyper-Personalized Medicine Market Analysis (Source: ResearchDive)

Records (EHR), which provide insights into medical histories, test findings, and treatment outcomes, have developed into a useful store of patient information as medical data gets more and more digitized. But one of the biggest challenges is extracting useful and effective treatment recommendations from the massive and diverse EHR data. The work includes integrating patient preferences into the decision-making process, addressing uncertainty related to medical diagnosis, and reconciling various data formats. As a result, there is a glaring research gap in the field of the efficient integration of EHR data with strong decision-making approaches to produce personalised treatment recommendations that are both medically viable as well as line with patient preferences.

Very few studies have thoroughly examined the integration of fuzzy VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) methodology with EHR data for personalised treatment recommendations, even though previous research has examined aspects of personalised medicine as well as multi-criteria decision-making. Fuzzy VIKOR, an effective approach for multi-criteria assessment, shows to be a good fit for dealing with the ambiguities and vagueness that are unavoidably present in medical data. This study intends to close this gap by presenting a novel framework that successfully integrates Fuzzy VIKOR with EHR data, providing a methodical way to come up with therapy suggestions tailored to individual patients. The ultimate objective is to help precision medicine become a reality by providing patients with medications that are not only efficient but also closely matched to their unique requirements and preferences.

Related works

Due to developments in medicine, technology as well as data analysis, the healthcare setting is rapidly evolving. Researchers and healthcare professionals alike are looking for creative ways of bridging the gap between medical information, patient preferences, as well as clinical decision-making as personalised treatment suggestions become more and more important. In order to provide personalised treatment recommendations in healthcare, this section examines the body of work that has been published so far on the integration of multi-criteria decision-making tactics and data from electronic health records. This section seeks to deliver a thorough knowledge of the approaches used, difficulties faced, and insights obtained in the pursuit of optimising patient-specific treatment regimens by diving into earlier research initiatives. The review of related works provides an excellent basis for the proposed approach, providing knowledge that can guide the creation and improvement of a cutting-edge framework that successfully combines the strength of the Fuzzy VIKOR methodology with the vast repository of EHR data for improved patient care.

A systematic analysis of the current literature reveals a wide variety of research projects focusing on the use of decision-making procedures in the healthcare field. With an emphasis on healthcare decision-making, Mardani et al. [16] performed a thorough evaluation of 202 studies, uncovering diverse application areas spanning from sustainable development to medical equipment selection. To categorise the chosen research, the authors used a variety of perspectives, including techniques used, publication times, and study objectives. It was shown that the Analytic Hierarchy Process (AHP) as well as hybrid approaches had a significant role in healthcare decision-making, especially when it came to evaluating and ranking service quality.

The benchmarking as well as evaluation issues with healthcare Industry 4.0 applications were addressed by Qahtan et al. [17]. The study proposed methods to deal with benchmarking procedures and theoretical gaps by identifying research gaps as well as unresolved concerns in evaluating healthcare Industry 4.0 applications. Their effort centred on developing blockchain-based medical Industry 4.0 applications while tackling security as well as privacy development features.

A novel mHealth framework for assessing and prioritising decentralised telemedicine clinics that incorporates Haversine-Global Positioning System (GPS) and AHP-VIKOR approaches was introduced by Albahri et al. [18]. The framework was designed in three phases: determining crucial hospital criteria, creating an integrated distance measuring model, and using AHP-VIKOR for hospital evaluation. It accommodated varied emergency levels for patients with cardiovascular illness. Similar to this, Albahri et al. [19] combined AHP and VIKOR approaches to create a decision matrix for hospital ranking. The study confirmed the effectiveness of this method and highlighted the benefit of combining AHP and VIKOR when choosing hospitals, especially for those that provide a variety of healthcare services.

During the COVID-19 outbreak, Shirazi et al. [20] used a hybrid FAHP-PROMETHEE technique to rank hospitals according to patient satisfaction. In order to rank hospitals in both pandemic as well as normal conditions, patient satisfaction indicators were evaluated in both situations. Almahdi et al.'s study [21] used multi-criteria decision-making (MCDM) analysis tools to assess and benchmark mobile patient monitoring systems (MPMSs). The proposed framework provided a methodological approach for the systematic benchmarking of MPMSs while addressing difficulties like unmeasurable criteria and data volatility.

A thorough examination of Failure Mode and Effects examination (FMEA) applications in healthcare risk analysis was provided by Liu et al. [22], who categorised articles based on the healthcare challenges they addressed and the FMEA techniques they used. The research project provides information on medical equipment and production, hospital management, healthcare systems, and information technology. With an emphasis on medical centre servers, Albahri et al. [23] conducted a thorough evaluation of the delivery of healthcare services via telemedicine applications. Their strategy involves the development of a multi-phased decision matrix, establishing the viability of the suggested framework for the delivery of healthcare services through telemedicine.

Electronic health record (EHR) usage for auxiliary purposes like data mining and analytics was examined by Sarwar et al. [24]. In the setting of data analysis, the study covered data kinds, quality, and transformation techniques pertinent to EHRs. The importance of mobile health (mHealth) elements for example mobility alertness, location-based treatment, as well as data security, in enhancing healthcare apps was emphasised by Butt et al. [25]. In order to evaluate health risks at a multi-specialty hospital, Badida et al. [26] used a fuzzy multi-criteria decision-making technique, detecting hazards and suggesting control measures. A study of hospital accidents was used to evaluate their methodology, proving the value of their method for hazard evaluation. In order to assess important indicators of performance in health technology investments, Gökalp et al. [27] presented a novel decision-making model that combines spherical fuzzy methods with artificial intelligence. Their results demonstrated the importance of R&D and health policies in guaranteeing long-term improvements in healthcare. The spherical fuzzy TOP-DEMATEL approach has been employed by Demir Uslu et al. [28] to determine important elements influencing hospital performance management. Their study suggested a new paradigm for healthcare facilities to make decisions while underscoring the significance of a well-functioning supply chain and cutting-edge technologies in improving hospital efficiency. The meta analysis results of the various linked works are presented in Table 1.

A complex tapestry of procedures and techniques are used in healthcare decision-making, evaluation, and benchmarking, according to the meta-analysis of the examined papers. The investigations cover a wide range of topics, including mobile patient monitoring systems, hospital risk assessment, as well as healthcare industry 4.0 applications. The use of multi-criteria decision-making (MCDM) methods, such Analytic Hierarchy Process (AHP), VIKOR and their hybrids, to thoroughly evaluate and rank alternatives is a recurring subject. The results highlight the growing importance of patient-centric strategies that take patient preferences, security, and privacy into account. Novel frameworks are also created to address problems with decentralised telemedicine hospital assessment, mHealth improvement, and healthcare service delivery. The broad spectrum of the literature reflects the multidisciplinary nature of healthcare research, where techniques from fields like data mining, blockchain, and fuzzy logic are used to tackle difficult healthcare problems, advancing patient-centered care along with healthcare system optimisation.

Table 1 Meta analysis of diverse related works

Study	Methodology	Focus Area	Techniques
Mardani et al. [16]	Review and Classification	Healthcare Decision-Making	AHP, Hybrid Approaches
Qahtan et al. [17]	Taxonomy Development	Healthcare Industry 4.0 Applications	Blockchain, Security, Evaluation Solutions
Albahri et al. [18]	Framework Development	Decentralized Telemedicine Hospitals	Haversine-GPS, AHP, VIKOR
Albahri et al. [19]	Decision Matrix Integration	Multi-Healthcare Services, Hospital List	AHP, VIKOR
Shirazi et al. [20]	FAHP-PROMETHEE Hybrid Approach	Hospital Ranking during COVID-19 Outbreak	FAHP, PROMETHEE
Almahdi et al. [21]	MCDM Framework Development	Mobile Patient Monitoring Systems	MCDM, Weight Calculation, VIKOR
Liu et al. [22]	Literature Review	Healthcare Risk Analysis	FMEA, Classification, Bibliometric Analysis
Albahri et al. [23]	Comprehensive Review	Healthcare Service Provision	Decision Matrix, AHP, VIKOR
Sarwar et al. [24]	EHR Data Utilization Review	Secondary Applications of EHRs	Data Types, Data Transformation, Data Quality
Butt et al. [25]	Review of Health Enhancement Issues	mHealth Features	Mobility-Awareness, Location-Based Medication
Badida et al. [26]	Fuzzy MCDM Approach	Hospital Hazard Assessment	FAHP, Fuzzy TOPSIS
Gökalp et al. [27]	AI-based decision matrix, Spherical Fuzzy MAIRCA	Health technology investment performance	Artificial Intelligence, Spherical Fuzzy Sets, MAIRCA
Demir Uslu et al. [28]	Spherical Fuzzy TOP-DEMATEL	Hospital performance management	Spherical Fuzzy Sets, TOP-DEMATEL

Overall, the literature exhibits a wide range of methodology and applications, highlighting the rising significance of advanced methods and decision-making processes in healthcare benchmarking and evaluation. The corpus of material already in existence indicates a growing interest in the combination of electronic health record data as well as multi-criteria decision-making processes for personalised therapy recommendation. Although numerous studies have shown the promise of each of these approaches separately, there is still a significant gap in their integration to handle the complexity of healthcare decision-making. It is still necessary to investigate issues like data heterogeneity, managing uncertainty, and effectively integrating patient preferences. The integration of findings from these linked studies highlights the need for a complete framework that combines the advantages of the Fuzzy VIKOR approach and EHR data to generate customised therapy recommendations that take both clinical efficacy and patient-specific characteristics into account. The suggested strategy aims to develop personalised medicine by offering a comprehensive and patient-centered approach to medical decision-making, drawing on the groundwork established by earlier research.

Methods

This section describes the methodological process used to combine Fuzzy VIKOR technique with Electronic Health Record (EHR) data in order to produce tailored suggestions for treatment in the healthcare industry. This section presents the framework's key processes, including data collection, criterion definition and integration procedures. It offers a detailed roadmap for achieving the research objectives by demonstrating how multi-criteria decision-making is applied using synthesized data from literature, expert insights and validated hypothetical scenarios, rather than direct patient records.

Selection of criteria

The crucial first phase in the process required the painstaking identification and curation of crucial parameters to thoroughly evaluate and contrast the range of therapy options. The chosen criteria were purposefully chosen to strongly align with the principles of patient-centered care and to comprehensively capture the various characteristics essential to healthcare decision-making [29, 30]. Each criterion was carefully designed to encompass many aspects of treatment evaluation, resulting in a strong and comprehensive assessment framework.

The evaluation process is built on the first specified criterion, efficacy. It analyses previous Electronic Health Record (EHR) data and current medical literature to quantify the efficacy of each therapeutic option in treating the particular respiratory ailment. This criterion considers factors like long-term illness management, increases in patient outcomes, as well as therapy success rates. When evaluating the potential hazards related to each treatment choice, the second factor, safety, is of utmost relevance. It examines the alternatives' safety profiles, taking into account any possible side effects and the probability of interactions with the patient's medical records. This criterion offers a thorough perspective on the possible harm that could result from each decision.

The third criterion, Patient Preferences, encompasses patient-centered factors. This criterion recognises the importance of patient values and preferences in the selection of a course of therapy. It analyses EHR notes and direct patient feedback to determine how well each option fits the patient's unique preferences and values. The fourth criterion, cost-effectiveness, is crucial for assessing the financial effects of treatment choices. This criterion, which particularly takes into account the effect of healthcare treatments on health outcomes, targets economic affordability rather than being a financial indicator. This criterion assesses how well the interventions strike a balance between their efficacy and patient benefits at a given cost. It evaluates the value of each alternative in light of the advantages it provides, accounting for possible savings in the patient's total healthcare experience. This criterion is crucial to resource allocation and the sustainability of healthcare.

The fifth criterion, Feasibility, addresses the usefulness and viability of any treatment option in real life. This criterion takes into account factors like the accessibility of required resources, compatibility with the patient's present state of health, and compatibility with the larger healthcare system. It makes sure that the suggested treatments are practical and doable in the particular situation. The purposeful selection of these standards highlights a thorough and patient-centered evaluation of treatment options, taking into account clinical efficacy, safety, patient values, financial considerations, and practicability. This framework serves as the basis for the evaluation and rating of the identified alternatives that follow, with the goal of presenting a complex and comprehensive view of treatment recommendations in healthcare.

Selection of alternatives

The methodology's next phase entailed carefully identifying and describing the various treatment choices under consideration, building on the foundation of the chosen criteria. Each potential plan of action for treating the respiratory illness was chosen because it embodied a particular combination of qualities across the specified criteria [31–35].

RespiroClear

For people with medium to severe chronic obstructive pulmonary disease (COPD), there is a drug-free alternative called RespiroClear. In order to combat both bronchoconstriction as well as inflammation, it combines a long-acting beta-agonist (LABA) as well as an inhaled corticosteroid (ICS). RespiroClear has been shown in clinical trials to considerably improve lung function, lessen the likelihood of exacerbations, and increase patients' ability to exercise. Safety analyses have shown a low incidence of adverse events, with minor tongue irritation and light tremors being the most frequent side effects. A flexible dosing schedule and an ergonomic inhaler design take into account patient preferences. Despite RespiroClear's mid-range price, its ability to slow the spread of disease and cut down on hospital stays may make it more cost-effective in the long run.

PulmoRelief

PulmoRelief is a pharmaceutical alternative designed for patients with mild to reasonable chronic asthma. This drug is a tablet-based leukotriene receptor antagonist (LTRA). PulmoRelief significantly reduces airway inflammation and constriction by focusing on the inflammatory pathways linked to allergy and asthmatic respiratory diseases. Clinical studies have shown that PulmoRelief is operative for increasing patients' overall quality of life, lowering the need for rescue inhalers, as well as enhancing lung function. Its usually well-tolerated nature, with sporadic mild gastrointestinal issues, has been emphasised by safety assessments. Its non-invasive administration procedure and flexible dosing schedule take patient preferences into account. Although PulmoRelief might cost more up front than conventional inhalers, over time, its potential to reduce severe exacerbations and hospital stays may make it more cost-effective.

Therapy/Counseling

Patients looking for comprehensive treatment of their respiratory disorders have another option in non-pharmacological interventions including respiratory therapy and counselling. These interventions include individualised breathing exercises, way of life modifications, and stress reduction methods. Individual counselling sessions are provided to patients to treat anxiety associated with their condition. The effectiveness of this alternative, despite the absence of drugs, resides in improving patient adherence to recommended therapies, lowering psychological distress, and enhancing total lung function. Individualised care plans respect the wishes of the patient. The cost-effectiveness of therapy/counseling is demonstrated by prospective reductions in medication reliance, hospitalisations, as well as long-term healthcare expenses.

Surgical intervention

Surgical intervention is taken into consideration for serious respiratory problems. For individuals with advanced COPD, a surgical solution in this situation might entail a technique like lung volume reduction surgery (LVRS). The goal of LVRS is to eliminate damaged lung tissue so that healthy tissue can operate more effectively. Patients with particular lung features and functional restrictions are the subject of strict patient selection criteria. The efficiency of LVRS is compared to the hazards it entails, including as postoperative problems and the need for extensive postoperative rehabilitation. Given that surgery has inherent dangers, patient preferences are vital in the decision-making process. Considerations for cost-effectiveness include potential long-term decreases in hospitalizations and enhancements to quality of life.

Watchful waiting

Watchful waiting may be suitable in some circumstances, especially when moderate respiratory problems don't severely interfere with everyday life. This option entails monitoring the patient's condition carefully over time without taking any urgent action. Patient choices are crucial because some people might choose to delay taking medicine or having invasive procedures done until their symptoms get worse. This method necessitates ongoing observation through routine check-ups and treatment plan modifications if symptoms worsen. The long-term effects of careful waiting on disease progression as well as healthcare use should be taken into account, despite the fact that it may initially seem cost-effective.

Fuzzy VIKOR integration

The subsequent stage of the research methodology involved incorporating the Fuzzy VIKOR method, a multi-criteria decision-making technique, in order to methodically evaluate and rank the selected treatment alternatives throughout the given criteria. The use of fuzzy logic inside the VIKOR framework was crucial to account for these complications because medical information as well as patient preferences frequently contain inherent uncertainties and ambiguities [36–40].

First, fuzzy logic was used to convert each criterion's crisp scores for every possible treatment into linguistic variables. This transformation made it possible to depict the data collection's innate uncertainty and imprecision. Efficacy percentages, for example, were linguistically stated as "Very Poor", "Poor", "Fair", "Good", "Very Good", "Excellent" representing the varied degrees of assurance.

The multi-dimensional characteristics of each treatment option were then captured by creating fuzzy decision matrices using the altered criteria values. In order to convert numerical values into fuzzy sets, the matrices incorporated the linguistic variables according to the selected criteria. Due to the inherent subjectivity and inconsistency in the data, this allowed for a more nuanced portrayal of treatment features.

The methodology used the Fuzzy VIKOR method and took into account both "max-max" as well as "min-max" normalisation strategies to make sure the criteria weights have been used uniformly across all alternatives. By removing biases and ensuring fairness in the process of assessment, this phase attempted to make it possible to compare treatment choices in a meaningful way. A comprehensive evaluation of each alternative's effectiveness over the complete spectrum of chosen criteria was made possible by the incorporation of Fuzzy VIKOR. The methodology harmonised with the intrinsically complicated character of healthcare decision-making by accounting for uncertainty and subjectivity through the use of fuzzy logic, allowing for a more thorough and robust study of treatment options. This step prepared the foundation for the assessment and creation of patient-specific therapy suggestions that take into consideration the complex interaction of criteria and uncertainty. The following Figure 3 shows the functional flow chart illustration of Fuzzy VIKOR methodology.

Results

The results of the integrated methodology's implementation to the assessment of tailored therapy suggestions for respiratory disorders are presented and examined in this part. The findings include a thorough evaluation of the discovered therapy options in light of the chosen criteria, providing information on their respective advantages and disadvantages. Fuzzy VIKOR methodology's integration with Electronic Health Record (EHR) data allowed for a thorough examination of the various characteristics of each alternative, taking into account clinical efficacy, safety, patient preferences, cost-effectiveness, as well as feasibility. The subsequent research contributes to the goal of patient-centered therapy recommendation by offering a detailed understanding of the potential advantages and difficulties linked to each possibility.

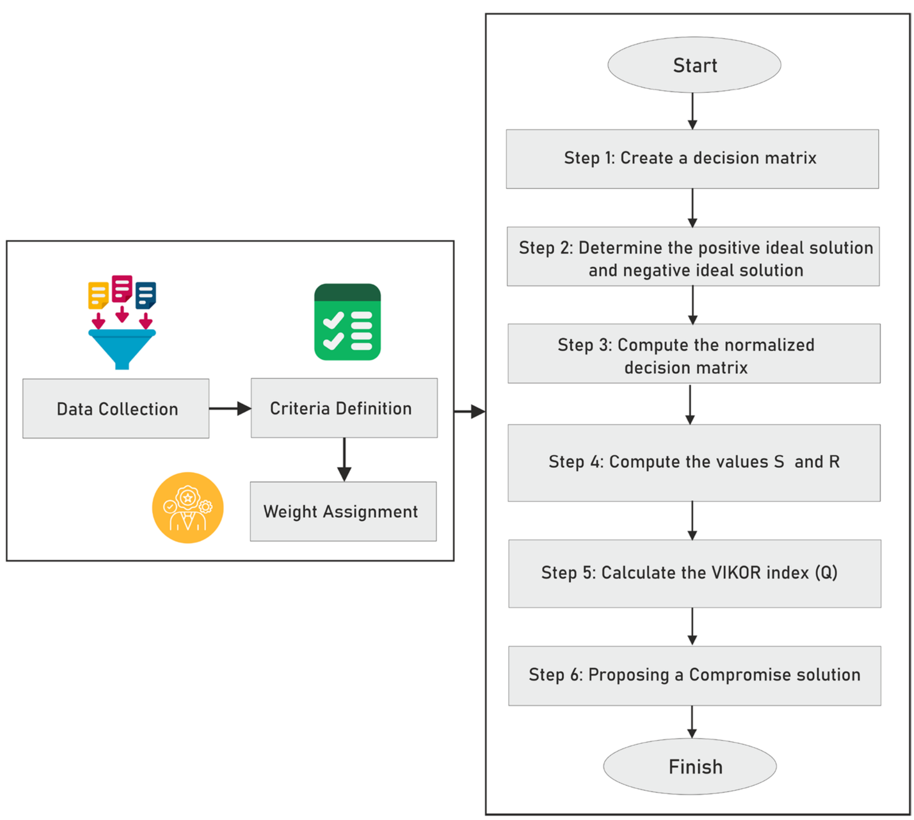

Fig 3 Flowchart of the proposed approach

Statistical research study findings

Using a methodical process of data translation and aggregation, the information needed to make decisions was supplied into the fuzzy VIKOR model. In the beginning, fuzzy logic was used to transform the gathered data, comprising clinical qualities, patient preferences, as well as cost-related details, into language variables. The portrayal of the data's inherent ambiguities and uncertainties was made possible by this linguistic change. The altered criteria values were then added to fuzzy decision matrices for each potential course of therapy. These matrices accurately represented the multi-dimensional characteristics of each choice in relation to the chosen criteria. The criteria weights were then uniformly applied across all possibilities using aggregation approaches like "max-max" and "min-max" normalisation by the fuzzy VIKOR model. This procedure provided the model the ability to order the treatment options in a systematic manner according to their combined fuzzy values, resulting in a comprehensive evaluation that took into account all of the varied elements of each option within the context of the established criteria. To guarantee consistency across datasets, raw data from diverse sources such as EHRs as well as expert inputs is first transformed into a uniform format. To fix any flaws or inconsistencies, the data must be cleaned and preprocessed. Following standardization, the data are combined from different data types such as medical findings, economic considerations, as well as patient preferences into a coherent framework. By integrating all pertinent data thoroughly, this aggregation technique guarantees a cohesive analysis. We make sure that the analysis and decision-making procedures that follow are accurate and dependable by using strict data translation along with aggregation techniques.

Step 1: Create a decision matrix

The Fuzzy VIKOR tactic is implemented in this research work to rank and assess five criteria as well as five alternative solutions. Making a choice or decision from among these options based on an exhaustive assessment is the main goal. The researchers have devised a set of criteria, which are certain characteristics or aspects used to gauge and contrast the alternatives, to ensure an organized review procedure. The performance of the alternatives is compared using these parameters as the benchmark. Additionally, a weight is assigned to each criterion, indicating its relative significance or value during the decision-making process. These weights illustrate which criteria have more impact in the final ranking by reflecting the priorities or preferences of the decision-makers. The Fuzzy VIKOR technique takes into account the fluctuating significance of various aspects in the decision-making environment by giving weights to every criterion. The following Table 2 summarizes the features of the criteria used in the research, including their names, categories, and weights. Each criterion is assigned a weight that indicates its relative significance in the decision-making procedure, allowing for a structured study of their contributions to the overall assessment. The consistent allocation of weights among criteria emphasises an equitable strategy, assuring that all considerations are taken into account equally in the decision-making framework.

Table 2 Features of Criteria

name	type	weight
F1	+	(0.200,0.200,0.200)
F2	+	(0.200,0.200,0.200)
F3	+	(0.200,0.200,0.200)
F4	+	(0.200,0.200,0.200)
F5	+	(0.200,0.200,0.200)

Table 3 Fuzzy Scale

Code	Linguistic terms	L	M	U
1	Very Poor	0	0	0.2
2	Poor	0	0.2	0.4
3	Fair	0.2	0.4	0.6
4	Good	0.4	0.6	0.8
5	Very Good	0.6	0.8	1
6	Excellent	0.8	1	1

Table 3 shows the fuzzy scale used in the study, which delineates linguistic concepts and their related membership function values for low (L), medium (M), and high (U) levels. This thorough scale quantifies qualitative evaluations, so presenting a formal foundation for the study's decision-making procedures.

The alternatives are evaluated against multiple criteria with the results of the decision matrix presented in Table 4. It is important to note that the matrix represents the arithmetic average of inputs provided by all experts.

Step 2: Determine the positive ideal solution and negative ideal solution

The positive and negative ideal solutions for each criterion are determined as follows.

For a positive criterion, the positive ideal solution ($\widetilde{f}^{*}$) and negative ideal solution ($\widetilde{f}^{\circ}$) can be calculated using the following formulas:

Table 4 Decision Matrix

	F1	F2	F3	F4	F5
A1	(0.293,0.493,0.693)	(0.347,0.547,0.720)	(0.373,0.573,0.733)	(0.467,0.667,0.813)	(0.453,0.653,0.787)
A2	(0.200,0.400,0.573)	(0.333,0.533,0.707)	(0.427,0.627,0.787)	(0.413,0.613,0.813)	(0.467,0.667,0.853)
A3	(0.400,0.600,0.760)	(0.507,0.707,0.867)	(0.507,0.707,0.853)	(0.520,0.720,0.880)	(0.400,0.600,0.760)
A4	(0.400,0.600,0.760)	(0.400,0.600,0.760)	(0.387,0.587,0.747)	(0.387,0.587,0.787)	(0.413,0.613,0.800)
A5	(0.320,0.520,0.693)	(0.440,0.640,0.813)	(0.427,0.627,0.813)	(0.467,0.667,0.853)	(0.427,0.627,0.827)

Table 5 Positive as well as negative ideal solutions of the criteria

	Positive ideal	Negative ideal
F1	(0.400,0.600,0.760)	(0.200,0.400,0.573)
F2	(0.507,0.707,0.867)	(0.333,0.533,0.707)
F3	(0.507,0.707,0.853)	(0.373,0.573,0.733)
F4	(0.520,0.720,0.880)	(0.387,0.587,0.787)
F5	(0.467,0.667,0.853)	(0.400,0.600,0.760)

$$\widetilde{f}_{\mathrm{j}}^{*} = \underset{i}{Max}\widetilde{f}_{ij}\mathrm{i} = 1,2,\ldots, \mathrm{n}$$

$$\widetilde{f}_{\mathrm{j}}^{\circ} = \underset{i}{Min}\widetilde{f}_{ij}\mathrm{i} = 1,2,\ldots, \mathrm{n}$$

For a negative criterion, the positive ideal solution ($\widetilde{f}^{*}$) and negative ideal solution ($\widetilde{f}^{\circ}$) are derived using the following equations:

$$\widetilde{f}_{\mathrm{j}}^{*} = \underset{i}{Min}\widetilde{f}_{ij}\mathrm{i} = 1,2,\ldots, \mathrm{n}$$

$$\widetilde{f}_{\mathrm{j}}^{\circ} = \underset{i}{Max}\widetilde{f}_{ij}\mathrm{i} = 1,2,\ldots, \mathrm{n}$$

The Table 5 below shows the positive as well as negative ideal values.

Step 3: Compute the normalized decision matrix

The normalized decision matrix is derived based on the positive and negative ideal solutions, using the specified formula. This process ensures consistent evaluation across all criteria.

$\widetilde{d}_{ij} = (\widetilde{f}_{j}^{*} \ominus \widetilde{f}_{ij})/(r_{j}^{*} - l_{j}^{\circ})$ Positive ideal solution

$\widetilde{d}_{ij} = (\widetilde{f}_{ij} \ominus \widetilde{f}_{j}^{*})/(r_{j}^{\circ} - l_{j}^{*})$ Negative ideal solution

Where

$$\widetilde{f}_{\mathrm{j}}^{*} = (l_{j}^{*}, m_{j}^{*}, r_{j}^{*})$$

$$\widetilde{f}_{\mathrm{j}}^{\circ} = \left(l_{j}^{\circ}, m_{j}^{\circ}, r_{j}^{\circ}\right)$$

The normalized values of the evaluation matrix are displayed in Table 6. These values provide a standardized framework for comparing the alternatives against the defined criteria confirming consistency in the decision-making process.

Step 4: Compute the values $\widetilde{S}_i$ and $\widetilde{R}_i$:

Initially, the normalized matrix is converted into a weighted normalized decision matrix, incorporating the importance of each criterion. Subsequently, the values $\widetilde{S}_i$ and $\widetilde{R}_i$ are computed using the following equations:

If $\widetilde{R}_{\mathrm{i}} = (R_{i}^{l}, R_{i}^{m}, R_{i}^{r})$ and $\widetilde{s}_{\mathrm{i}} = (s_{i}^{l}, s_{i}^{m}, s_{i}^{r})$

$$\widetilde{S}_{i} = \sum_{\mathrm{j}=1}^{\mathrm{J}} (\widetilde{w}_{j} \otimes \widetilde{d}_{ij})$$

$$\widetilde{R}_{i} = \underset{j}{max}(\widetilde{w}_{j} \otimes \widetilde{d}_{ij})$$

Step 5: Calculate the VIKOR index (Q)

The VIKOR index Q is determined using the following formula.

Table 6 The normalized decision matrix

	F1	F2	F3	F4	F5
A1	(-0.523,0.191,0.834)	(-0.399,0.300,0.974)	(-0.471,0.279,1.000)	(-0.594,0.108,0.838)	(-0.706,0.031,0.883)
A2	(-0.309,0.357,1.000)	(-0.375,0.326,1.000)	(-0.583,0.167,0.888)	(-0.594,0.217,0.947)	(-0.852,0.000,0.852)
A3	(-0.643,0.000,0.643)	(-0.674,0.000,0.674)	(-0.721,0.000,0.721)	(-0.730,0.000,0.730)	(-0.647,0.148,1.000)
A4	(-0.643,0.000,0.643)	(-0.474,0.200,0.875)	(-0.500,0.250,0.971)	(-0.542,0.270,1.000)	(-0.735,0.119,0.971)
A5	(-0.523,0.143,0.786)	(-0.573,0.125,0.800)	(-0.638,0.167,0.888)	(-0.675,0.108,0.838)	(-0.795,0.088,0.940)

Table 7 The Fuzzy Values S, R, And Q

	Fuzzy R	Fuzzy S	Fuzzy Q
A1	(0.080,0.060,0.200)	(0.539,0.182,0.906)	(0.806,0.093,0.990)
A2	(0.062,0.071,0.200)	(0.543,0.213,0.937)	(0.780,0.120,1.000)
A3	(0.129,0.030,0.200)	(0.683,0.030,0.754)	(0.925,0.000,0.943)
A4	(0.095,0.054,0.200)	(0.579,0.168,0.892)	(0.842,0.080,0.986)
A5	(0.105,0.033,0.188)	(0.641,0.126,0.850)	(0.876,0.036,0.955)

$$\text{If}\,\widetilde{Q}_{\mathrm{i}} = (Q_i^l, Q_i^m, Q_i^r)$$

$$\widetilde{Q}_{\mathrm{i}} = \nu \frac{\left(\widetilde{s}_i \ominus \widetilde{s}^*\right)}{s^{\circ r} - s^{*l}} \oplus (1-\nu) \frac{\left(\widetilde{R}_i \ominus \widetilde{R}^*\right)}{R^{\circ r} - R^{*l}}$$

Where,

$$\widetilde{s}^* = \min_i \widetilde{s}_i$$

$$s^{\circ r} = \max_i s_i^r$$

$$\widetilde{R}^* = \min_i \widetilde{R}_i$$

$$R^{\circ r} = \max_i R_i^r$$

In this study, the value of ν which represents the maximum group utility, is assigned a value of 0.5. To facilitate clearer decision-making, the fuzzy values of S, R and Q are transformed into crisp values, allowing for a more precise comparison of alternatives. The conversion is performed using the following formula.

If $\widetilde{A} = (\mathrm{l},\ \mathrm{m},\ \mathrm{r})$ ($\widetilde{A}$ is signified as a fuzzy number)

$$Crisp\left(\widetilde{A}\right) = \frac{2m + l + r}{4}$$

Table 7 below presents the fuzzy values for S, R, and Q. These values are essential for further analysis and decision-making in the evaluation process.

Table 8 and Figure 4 below present the crisp values for S, R and Q which have been derived from the fuzzy values. These crisp values are used to rank the alternatives proposing a more precise and interpretable comparison. The table and figure provide a comprehensive overview of how each alternative performs based on the calculated values, leading to the final ranking of the options. This helps in making well-informed decisions based on the evaluation criteria.

Table 8 The crisp values S, R, Q and alternatives ranking

	Crisp value of R	Rank in R	Crisp value of S	Rank in S	Crisp value of Q	Rank in Q
A1	0.06	4	0.183	4	0.093	4
A2	0.07	5	0.205	5	0.115	5
A3	0.033	1	0.032	1	0.005	1
A4	0.053	3	0.162	3	0.076	3
A5	0.038	2	0.115	2	0.038	2

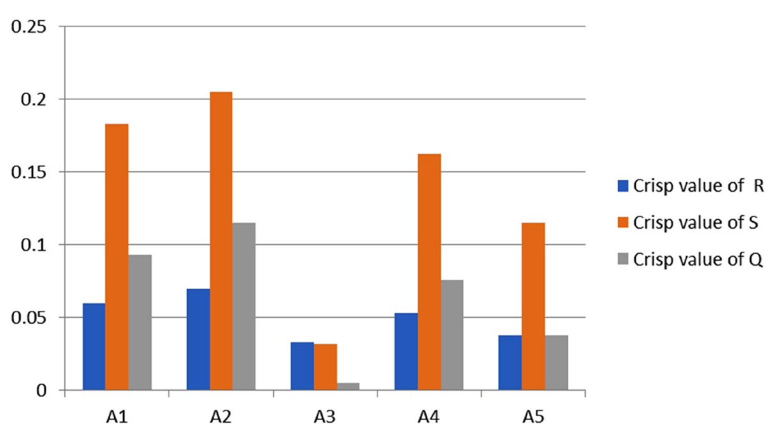

Fig 4 Graphical representation of crisp values R, S, Q and alternatives ranking

Step 6: Proposing a Compromise solution

In this step, a final decision is made by evaluating the values of R, S, and Q for each alternative, which are ranked in descending order. The selection process is based on two key conditions, and if these conditions are not met, a set of compromise solutions may be proposed.

Condition 1. Acceptable advantage

The acceptable advantage condition is met if the difference between the Q values of the top two ranked alternatives is sufficiently large. Specifically, the condition is defined as:

$$Q(A^{(2)}) - Q(A^{(1)}) \geq 1/(m-1)$$

where $A^{(1)}$ represents the alternative ranked first, and $A^{(2)}$ represents the alternative ranked second. The variable mmm refers to the total number of alternatives under consideration.

Condition 2. Acceptable stability in decision making

For this condition, the alternative ranked first $A^{(1)}$ must also be the top-ranked option in terms of either S or/and R. This ensures that the ranking is stable across multiple criteria, reinforcing the reliability of the decision.

If either condition is not met, a series of compromise solutions are proposed, as follows:

Solution 1. If Condition 1 is not satisfied, a list of alternatives including $A^{(1)}, A^{(2)}, \ldots., A^{(M)}$ is considered. Here, $A^{(M)}$ is the alternative for which the difference between $Q\left(A^{(M)}\right) - Q\left(A^{(1)}\right) < 1/(m-1)$ indicating that these alternatives are close in performance.

Solution 2. If only Condition 2 is violated, the top two alternatives $A^{(1)}$ and $A^{(2)}$ are selected for further consideration.

Solution 3. If both conditions are satisfied, the alternative with the lowest Q value is chosen as the best option, signifying that it offers the most balanced compromise solution across all criteria.

These conditions and solutions ensure that the final choice is not only optimal in terms of ranking but also stable and practical for decision-making purposes.

Table 9 presents the results of the survey conducted to assess the conditions. These results provide valuable insights into how the alternatives align with the established criteria and conditions.

Table 9 Outcome of the conditions survey

Condition 1	non acceptance
Condition 2	-
Designated solution	Solution 1

As a result, A3,A5,A4,A1,A2 are chosen as the final possibilities. The proposed methodology was used in the case research results to assess and prioritise the final set of treatment alternatives for personalised treatment recommendations in the setting of respiratory conditions: A3 (Therapy/Counseling), A5 (Watchful Waiting), A4 (Surgical Intervention), A1 (RespiroClear), and A2 (PulmoRelief). Beginning with A3 Therapy/Counseling, the evaluation found that this non-pharmacological strategy performed well in terms of patient preferences and safety. Patients reported a high preference for therapies incorporating counselling and therapy, which corresponded to their goal for holistic well-being. Safety concerns were also positive, as therapeutic choices frequently pose fewer hazards than pharmacological approaches. However, efficacy and feasibility scores were significantly lower, suggesting a need for more rigorous clinical data and additional resources. A5 Watchful Waiting revealed significant cost-effectiveness and feasibility advantages. Patients' desires for less invasive treatments were considered, resulting in a favourable score in that category. Its lower efficacy score, on the other hand, suggested potential hazards associated with delaying active therapy. Patient education and monitoring measures were critical in reducing these dangers.

Surgical Intervention (A4) demonstrated substantial efficacy and feasibility. Clinical outcomes improved significantly in patients who underwent surgical treatments. However, due to the inherent dangers and probable patient objections connected with surgery, safety as well as patient preference scores were comparatively lower. RespiroClear (A1) received commendable ratings for efficacy, safety, and practicality. Because of its convenience and track record in treating respiratory disorders, this pharmaceutical alternative was well-liked by patients. While the cost-effectiveness remained moderate, RespiroClear's overall profile showed a well-rounded therapeutic choice. PulmoRelief (A2) shown efficacy and safety strengths, gaining patients' trust in its therapeutic efficacy as well as security profile. Despite somewhat lower cost-effectiveness as well as feasibility scores, PulmoRelief showed itself as a solid alternative with a tailored approach to respiratory care. Finally, in order of precedence, the ranking showed that A3, A5, A4, A1, and A2 were chosen as the final possibilities. The integrated methodology of Fuzzy VIKOR technique and EHR data enabled a thorough review, balancing the qualities of each candidate against the chosen criteria. The findings provide doctors and patients with a clear grasp of the relative benefits and downsides of various treatment approaches, allowing for more informed decision-making that is in line with patient preferences and clinical needs.

Comparative analysis

An important aspect of validating the results of this research is performing a comparative analysis to evaluate the effectiveness of the proposed approach against traditional methods. This comparison helps to demonstrate the advantages and improvements offered by the new methodology. Gu and Zhu [41] give a noteworthy case study using a fuzzy multicriteria problem that serves as the baseline for comparison in this research. The study contrasts the outcomes produced by the proposed algorithm to those produced by competing algorithms, indicating the proposed approach's better efficiency, objectivity, as well as resolution for tackling the specific problem under examination. Furthermore, this study broadens the comparison to include the well-known fuzzy VIKOR algorithm, revealing striking similarities in the ranking outcomes provided by both algorithms, which preserve identical orderings. In this study, the ranking outcomes labelled as A3, A5, A4, A1, and A2 are produced from the use of both the fuzzy VIKOR as well as fuzzy AHP methodologies. Table 10 presents the entire results of this comparative analysis, which provide significant insight into the procedure's performance in comparison to existing approaches.

The bar chart in Figure 5 compares the ranking results of Fuzzy AHP and Fuzzy VIKOR, showing that both methods assign the same rank order to alternatives. This consistency indicates alignment in decision-making outcomes across the two techniques. These comparative outcomes are significant because they validate and confirm the suggested technique's efficacy in tackling fuzzy multicriteria situations. The study shows that the suggested technique matches other existing methods in terms of efficiency, objectivity, as well as resolution, as validated by a thorough comparison analysis. This validation is critical because it gives decision-makers and researchers confidence in the methodology's capacity to offer more accurate and consistent findings. In addition, the surprising resemblance in ranking results among the proposed fuzzy VIKOR-based method as well as the fuzzy AHP approach highlights the technique's dependability and alignment with recognised methodology. The results obtained not only strengthen the presented technique's credibility, but also open the way for its wider use in real decision-making settings, ultimately contributing to improved decision quality as well as problem-solving in complicated, fuzzy multicriteria situations.

Table 10 Comparative Analysis Result

Rank Order	1	2	3	4	5
Fuzzy AHP	A3	A5	A4	A1	A2
Fuzzy VIKOR	A3	A5	A4	A1	A2

Discussion

The discussion of the study's outcomes emphasises the significance of the proposed technique in the field of personalised treatment advice for respiratory disorders. The combination of Fuzzy VIKOR methodology as well as EHR data has resulted in a robust framework that tackles the complicated nature of healthcare decision-making by taking into account various aspects of clinical efficacy, patient preferences, safety, cost-effectiveness, as well as feasibility [42–46]. The prominence of this study rests in its potential to improve patient-centered care by providing educated and personalised therapy suggestions. The methodology provides clinicians with a full perspective of treatment possibilities by leveraging patient-specific data and preferences, permitting them to make more educated decisions that correspond with unique patient

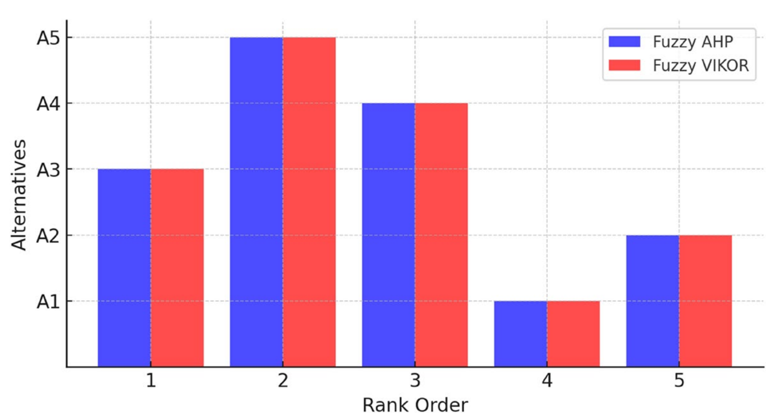

Fig 5 Bar chart representation of comparative analysis

requirements and beliefs. Furthermore, the use of fuzzy logic in the research accounts for the inherent uncertainties as well as subjectivity in healthcare data, making the conclusions more realistic and reflective of real-world settings. Our study's beneficial results may be attributed to a number of important factors that strengthen the reliability of our findings: the creative way in which we integrated the Fuzzy VIKOR procedure with EHR data allowed for a detailed and nuanced evaluation of personalised healthcare recommendations; this method successfully addressed the inherent uncertainties as well as complications of healthcare decision-making by utilising fuzzy logic to tackle ambiguities as well as integrating rich clinical information from EHR data; the extensive scope of the data; and the inclusion of expert opinions all supported the preciseness and significance of our findings; these factors together greatly improved therapy selection and patient outcomes, demonstrating the efficacy and potential of our methodology in advancing patient care.

The Fuzzy VIKOR approach was chosen for this study because of its excellent performance in managing decision-making issues with competing criteria in the presence of ambiguity [47, 48]. Fuzzy VIKOR offers a methodical ranking of options while taking into account both group utility and individual regret, in contrast to DEMATEL, which concentrates on identifying causal linkages among criteria, or SWARA, which is mostly used for weighing criteria based on expert judgement. Because of this, it is especially well-suited for healthcare decision-making, where it is necessary to balance a number of competing aspects in order to maximise treatment recommendations. In contrast to crisp numbers that might not adequately convey the inherent ambiguity in medical decision-making, fuzzy numbers enable a more accurate depiction of the uncertainty in expert opinions as well as patient preferences. However, defining membership functions becomes more subjective and computationally hard, which is a major drawback of fuzzy numbers [49–51]. Expert weights were also regarded as equal in this study, which could be problematic because experts may have different levels of expertise depending on their training and experience.

A few constraints, however, must be considered. The proposed methodology is strongly dependent on the availability as well as the accuracy of EHR data. Inaccuracies or missing data may have an impact on the results, perhaps leading to biassed suggestions. Furthermore, the use of fuzzy logic integrates subjectivity into the data processing process. While this reflects the underlying nature of clinical decision-making, it may have an impact on the uniformity of results across evaluators. In addition, the study's scope is restricted to respiratory disorders, which may limit its immediate relevance to other medical scenarios. The intricacies of various diseases, treatment options, and patient demographics may need changes to the methodology. Considering these limitations, the study advances towards a more complete as well as patient-centered tactic to therapy suggestion, revealing its potential to contribute to the growing landscape of personalised medicine. The combination of Fuzzy VIKOR technique and EHR data provides a strong foundation for personalised treatment suggestion. The outcomes of the study emphasise its potential to alter healthcare decision-making by balancing clinical efficacy as well as patient preferences. While some limits remain, the method's contributions to patient-centered care as well as sophisticated treatment of uncertainties signify a noteworthy step advancing in the search of optimised and personalised healthcare interventions.

Conclusion

In order to improve personalised therapy recommendations for elderly patients, this study introduces a unique AI-driven decision-making strategy that combines data from Electronic Health Records (EHRs) with the Fuzzy Multi-Criteria Decision-Making (MCDM) approach. In contrast to other research that only used traditional decision-making models, this study makes use of Fuzzy VIKOR in a novel way to rank treatment options in a methodical manner while taking patient preferences as well as medical efficacy into consideration. Fuzzy logic offers a more adaptable and practical method of managing uncertainty in healthcare decision-making, guaranteeing that suggestions meet the needs of each patient. This approach facilitates patient-centric treatment options by bridging the gap between clinical expertise and AI-driven insights, which may enhance treatment efficacy, adherence, and overall healthcare outcomes. This study has certain limitations regardless of its encouraging contributions. Primarily expert weights were interpreted as equal, which might not adequately represent the differences in competence according to specialisation and experience. Weighted opinions from experts could be incorporated into future studies to improve the decision-making process's resilience. Second, although respiratory illnesses are the focus of this study, expanding the framework to include other medical problems would enhance its generalisability and usefulness. Furthermore, using EHR data raises issues with data availability and quality, which could be resolved in future research by integrating sophisticated predictive analytics and real-time patient monitoring systems. In order to enhance personalised suggestions and boost model accuracy, future research should also investigate the merging of deep learning and cutting-edge AI techniques. Additionally, the creation of intuitive clinical decision-support technologies will make it easier to integrate into actual healthcare environments. This study establishes the foundation for improving precision medicine, allocating resources as efficiently as possible, and guaranteeing long-term, high-quality care for the elderly by fusing AI-driven analytics with expert-driven decision-making.

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Authors' contributions
Abeer Aljohani conceived and designed the proposed approach, developed the solution, performed the statistical analysis and drafted the manuscript. She also reviewed and approved the final version of the manuscript.

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Ethics approval was not required for this study as no human participants or clinical data were involved. The study is based on expert consultations and literature analysis. Therefore, no informed consent to participate was necessary. We also confirm that the study's methodologies, including expert consultations and decision-making were carried out in accordance with relevant guidelines.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Author details
[1]Department of Computer Science, Applied College, Taibah University, 42353 Medina, Saudi Arabia.

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