ARTICLE

Cite This: J. Of. Comp. Sci. and Data Eng.2025, 2, 80-91

Sciforce

Journal of Business Intelligence and Data Analytics

Journal homepage: www.sciforce.org

Transforming Medicine: The Rise of Diagnostic Aid Applications Using the WSM Method

Mr.Vedaswaroop Meduri*

Full Stack Lead, Laboratory Corporation of America, Illinois, USA

ARTICLE INFO

Article history:
Received: 20250105
Received in revised form: 20250118
Accepted: 20250118
Available online: 20250130

Keywords:
Medical Diagnosis;
Expert Systems;
WSM (Weighted Sum Method);
Healthcare Technology;
Diagnostic Accuracy.

ABSTRACT

Rough set theory has been widely applied in medical diagnosis to address uncertainty and enhance accuracy. However, most studies overlook identifying critical symptoms, such as those for pneumonia, and fail to propose a decision rule base centered on essential attributes. This research focuses on reducing unnecessary symptoms and identifying core pneumonia indicators using linguistic terms. It also introduces a decision rule base to improve diagnostic precision and support effective decision-making, presenting a promising approach for advancing medical diagnostics.

This research contributes to advancing pneumonia diagnostics by addressing gaps in prior studies that neglect core symptom identification and rely heavily on deterministic methods. By leveraging linguistic terms and rough set theory, the study aims to identify essential symptoms and reduce redundancies. The resulting decision rule base supports accurate, efficient diagnostic processes.

Full Stack Tech Lead, Software Engineering Manager, Principal Engineer – AI Solutions, Senior Solution Architect,Cloud Infrastructure Specialist. Evaluation parameters: Clarity, Market Relevance, Vagueness, Misleading Scope.

The results Full Stack Tech Leadattained the greatest rank, yet Senior Solution Architect it reaches the lowest rank.

"Full Stack Tech Lead has the highest value for Diagnostic Assistance Applications according to the WSM approach".

Keywords: Medical Diagnosis, Expert Systems, WSM (Weighted Sum Method), Healthcare Technology, Diagnostic Accuracy.

*Corresponding author. Tel.: +1 (312) 576-4147; e-mail: ved.workemail@gmail.com

Introduction

Previous studies utilizing rough set theory for medical diagnosis have explored advanced methods to address uncertainty and develop high-accuracy diagnostic models. However, these studies do not focus on identifying the critical symptoms for pneumonia. Additionally, none have proposed a decision rule base centered on the essential set of attributes. Most research also relies on deterministic data analysis, while in medical diagnostics; symptoms are often described using linguistic terms to express severity. This study aims to reduce unnecessary symptoms and identify the core symptoms of pneumonia using an information table with linguistic terms. A decision rule base is created to support pneumonia diagnosis, enhancing diagnostic accuracy.

In summary, the approach identifies the core symptoms of the disease, assesses their importance, and creates a decision support system to aid the diagnostic process. The structure of the paper is as follows: The materials and methodology are covered in Section 2, while Section 3 presents a numerical computation for pneumonia diagnosis, followed by an outcome analysis of the proposed approach. A comparative analysis of results and a discussion is provided next, followed by the limitations of the research. The paper concludes with a final summary.[2] Online AI symptom checkers and diagnostic assistants (DAs) offer the potential to improve the quality, accessibility, and convenience of care while lowering healthcare expenditures and misdiagnosis.

This is only possible, though, if they work with great accuracy. Both Bayesian Networks (BNs) and Machine Learning (ML) have limitations when used for general medical diagnosis, despite their potential in the healthcare industry. Despite significant progress in using machine learning in some biomedical fields, challenges persist in using it for broader medical diagnosis. These challenges include difficulty in modeling causal inference, understanding semantic relationships (such as subtypes like "is-a" and "part-of"), logic, and heuristics, as well as issues with interpretability. Additionally, there are difficulties in appropriately addressing missing or incomplete data, label leakage, biases, and erroneous labels when DAs are being trained or educated with data from electronic medical records.

In order to reduce legal risks, EMRs are primarily made to support and document care and reimbursement, not to precisely characterize medical conditions.[3] With the rapid advancement of hospital information systems, patient data has been continuously accumulated, providing a solid foundation for the development of disease diagnostic expert systems. However, the challenge of quickly and effectively building a comprehensive knowledge base is recognized as a major obstacle in expert systems. Data mining technology is a powerful tool for analyzing and extracting valuable insights from large datasets, and it has found widespread application across various fields. Classification and prediction methods within data mining can automatically derive generalized descriptions from historical data, enabling the prediction or classification of future data. The emergence and application of these methods align with the current shift in medicine from empirical and experimental approaches to evidence-based medicine, and they are increasingly being integrated into medical diagnostic practices.

Therefore, research into tumor diseases is of great importance to humanity, with early detection and treatment being key to improving the cure rates for such conditions. [4] In developed nations, breast cancer is the most prevalent malignant disease and the second most common type of cancer among women. Due to their high sensitivity, MRI-based techniques like dynamic contrast-enhanced MRI (DCE MRI), or more generally breast MRI, and MR spectroscopy (MRS) have become powerful diagnostic tools in addition to standard imaging techniques like X-ray mammography and sonography for screening and diagnosis. In some situations, further imaging techniques such as scintigraphy and positron emission tomography are employed to increase specificity. Breast cancer diagnosis and detection have been greatly impacted by the use of breast MRI. Although X-ray mammography is still the most used method for screening and diagnosis in clinical settings, breast MRI has benefits because of its increased sensitivity and lack of dangerous radiation. [5] The demand for automated, real-time medical services for emerging diseases is driving efforts to develop a ubiquitous healthcare monitoring system.

Furthermore, this system's collection and storage of physiological data is essential for early warning and diagnosis. A Wireless Health Advanced Mobile Bio-diagnostic System (WHAM-BioS) has been proposed to increase diagnostic accuracy and medical services. In addition to introducing novel clustered sensor network (CSN) architecture intended for long-term, periodic tableware applications, this study highlights the network and communication technology within WHAM-Bio's.The human body gateway (HBG), a specialized device, houses most of the network operations in the suggested CSN architecture. It is the duty of the sensor nodes to detect and communicate their findings to the HBG. The architecture suggests a number of protocols that allow each HBG to establish a contention-free environment for its sensor nodes, therefore minimizing design complexity and lowering implementation costs. [6] Based on statistical learning theory, the Support Vector Machine (SVM) is a sophisticated and potent machine learning method that works especially well with limited sample sizes, nonlinearity, high dimensionality, and local minima.

The electrocardiogram (ECG) is essential for the clinical identification of cardiac disorders, which provide serious health hazards to people. Both internal and external researchers have been actively investigating the use of computers for the precise and quick diagnosis of heart disease. Therefore, it is crucial to investigate faster and more accurate automatic ECG analysis techniques. This study suggests using SVM for the clinical diagnosis of heart disorders. Eight-lead ECGs in series and parallel are the two ECG sample input patterns taken into consideration. A Pentium 350 MHz CPU with 512 MB of RAM powers all tests, and Mat lab 6.5 is utilized to solve the quadratic programming. An SVM-based comparison of the two input patterns reveals that the parallel input approach produces incredibly accurate and dependable results, with considerable promise for clinical diagnosis applications. [7] One issue is the poor acceptance by frontline clinicians who face unforeseen implementation challenges that disrupt their workflow, reduce the time available for patient care, and impede interoperability, causing frustration.

Health-care providers are likely to be skeptical about the value of health tools if they are not interoperable, meaning the data they generate cannot be integrated with other clinical information or accessed via electronic health records. Another challenge is the lack of high-quality evidence supporting the effectiveness of diagnostic and treatment tools, which both providers and sponsors may rightfully question. Reports from other sectors show that many health projects, despite starting with promise, often remain in the pilot phase or fail to be sustained.[8] A telematics-based system called DIAGNOSIS was created to help with the processing, management, and computer-assisted interpretation of medical pictures. By providing tools for segmenting and doing quantitative analysis of pertinent organs or lesions, its user-friendly interfaces and sophisticated image-processing capabilities improve the diagnostic process. Along with capabilities for effective data management, the system also has a relational database that houses the patient's tomographic images and other pertinent data, including demographics.

This streamlines the process of managing and storing images, and the telematics elements of the system facilitate communication between distant medical specialists.[9] The goal of this study was to create a prototype expert system that would help patients identify their ailments and provide them the right counsel. It also looks at how the expert system uses knowledge management. Finding an efficient language to convey a patient's medical history and present state in a knowledge base so that the expert system may conduct consultations effectively was one of the study's main goals. To record the required knowledge, production rules were used. A CLIP (C Language Integrated Production System) with a Java interface was used to create the expert system. The system's analysis of medical situations yielded positive results, consistently identifying the proper diagnosis. [10] Applications for fault diagnosis are being used more often in a variety of industries. Detecting car failures is a diagnostic procedure that calls for specialized knowledge. One well-known Artificial Intelligence (AI) method for handling these kinds of tasks is the Expert System (ES). The prerequisites for developing effective Knowledge-Based Systems (KBS) for this purpose are outlined in this study, along with the necessity of an ES in developing an automobile failure detection model.

It also shows how the Car Failure and Malfunction Diagnosis Assistance System (CFMDAS) was developed using the ES. However, obtaining the data required to create the knowledge base and carry out inference is one of the many obstacles facing the development of CFMDAS.Furthermore, diagnosing auto problems requires extremely technical knowledge, and qualified mechanics are frequently expensive and hard to find. In order to help mechanics with failure diagnosis and training, solutions such as CFMDAS can be quite helpful. Additionally, more accurate and effective models result from the capture and preservation of important knowledge in this field. [11] There are several obstacles and problems involved in diagnosing auto breakdowns and malfunctions. The procedure is intricate and involves a number of heuristic tasks that call for specific knowledge and abilities. When the failure happens in an area where there isn't immediate support, having a basic toolkit and assistance software is essential to helping drivers at least determine the origin of the problem. This enables drivers to evaluate the state of their car and try to fix the issue on their own. Machines are frequently equipped with diagnostic expertise through the use of expert systems. Still, research is being done to improve the accuracy and inference powers of expert systems.

Therefore, this work presents Automated Car Failure detection Assistance (ACFDA), an agent-based inference engine for the expert system for auto failure detection. [12] Rare diseases are frequently difficult for non-specialist personnel to identify, and the Minority Disease Diagnostic Assistant (Midia) tool has the potential to significantly improve early detection of these conditions. It facilitates the referral process to the appropriate specialists by enabling faster and more accurate diagnoses. This reduces the amount of time needed for diagnosis ensuring that specific treatments can begin sooner, which is crucial for preventing complications and improving treatment effectiveness. As a result, it contributes to more efficient and personalized healthcare.[13] The most widely used laboratory diagnostic procedures typically involve analyzing the cellular and chemical components of blood.

However, other biological fluids, such as saliva, offer unique advantages. Whole saliva can be collected non-invasively and by individuals with minimal training, without the need for special equipment. Using saliva for disease diagnosis could be particularly beneficial for children and older adults, as it presents fewer compliance issues compared to blood collection. Additionally, saliva analysis may offer a cost-effective method for screening large populations.[14] High-quality and adequate quantities of condition monitoring data are necessary for deep learning-based methods for autonomous industrial fault detection and diagnosis (FDD). However, data gathering is frequently restricted in real-world industrial settings, which leads to sparse and inadequate data for training a data-driven model. In order to address this issue, this paper presents a novel approach that makes use of multimodal data and domain expertise to create a data-driven solution. For complex machines, where single-source Multimodal data can provide supplementary insights, as sensors might not be able to record all pertinent health information.

However, before these data can be used successfully, the previously described issues need to be resolved. Even with low data volumes, the multimodal learning approach described in this methodology can extract useful information from many data sources and domain expertise.[15] Because cancer cells release more exosomes into the serum than healthy cells do, and because these exosomes overexpress specific cancer-related biomarkers, exosomes have attracted growing attention in blood-based diagnostics. However, there are many technological obstacles in the way of extracting and evaluating exosome biomarkers for therapeutic application. In this work, we created a microfluidic chip that allows for the immune system to capture and measure circulating exosomes from tiny sample volumes. We then used this technology in a clinical investigation.

To help in diagnosis, circulating EpCAM-positive exosomes were quantified in three healthy controls and six patients with breast cancer.[16] Data from many monitoring equipment is used by protection engineers to diagnose post-fault disturbances. Various intelligent systems have previously been created to analyse this data and provide engineers with insights to help with the diagnosis process. However, because system integration is difficult, the majority of these systems continue to operate independently. Multi-Agent Systems are proposed in this work as a scalable and adaptable substitute for existing integration techniques. [17] Handheld computers, or Healthcare professionals are using personal digital assistants (PDAs) more and more in their regular work. Finding timely, reliable, and easily accessible pharmacological information has proven to be a major difficulty for doctors, chemists, nurses, and healthcare students. Healthcare professionals may now access data at the point of care thanks to the handheld computer, which has revolutionized the way they retrieve medication information. Among the primary difficulties with using PDAs is the large number of medication applications available, making it difficult for healthcare providers to choose the right one. Additionally, software now includes patient-tracking applications that simplify patient monitoring, as well as tools for accessing formulary information.

Materials and method

Alternatives:

Full Stack Tech Lead:

A Full Stack Tech Lead is responsible for overseeing and guiding a development team in building applications across the full technology stack, including front-end, back-end, and database. They lead by example in coding, ensuring high-quality deliverables, architecting solutions, mentoring team members, and bridging communication between business stakeholders and developers.

Software Engineering Manager:

A Software Engineering Manager focuses on managing software development teams, setting goals, tracking progress, and fostering a collaborative environment. They are responsible for hiring, coaching, and evaluating engineers, defining team processes, and aligning development efforts with business objectives while ensuring timely delivery of high-quality software.

Principal Engineer – AI Solutions:

A Principal Engineer – AI Solutions is a senior technical expert who leads the design, development, and deployment of advanced AI and machine learning solutions. They define strategies for AI-driven products, guide research and implementation, collaborate with cross-functional teams, and ensure that AI technologies meet performance, ethical, and scalability standards.

Senior Solution Architect:

A Senior Solution Architect is responsible for designing and implementing high-level technical solutions that meet the strategic needs of an organization. They analyze requirements, create system blueprints, and ensure that solutions are scalable, reliable, and aligned with both technical and business goals while collaborating closely with stakeholders.

Cloud Infrastructure Specialist:

A Cloud Infrastructure Specialist designs, implements, and maintains cloud-based infrastructure. They ensure optimal performance, security, and scalability of cloud environments, often working with platforms like AWS, Azure, or Google Cloud. Their responsibilities include managing cloud architecture, automation, cost optimization, and supporting development teams with infrastructure needs.

Evaluationparameters:

Clarity:

The quality of being clear, precise, and easily understood. It ensures that information, ideas, or instructions are presented in a way that leaves little room for confusion or misinterpretation.

Market Relevance:

The extent to which a good, service, or concept satisfies the demands of the present preferences, or demands of the target market. It indicates how aligned something is with market trends, consumer behavior, or competitive positioning.

Vagueness:

The state of being unclear, imprecise, or lacking specific details. Vagueness often leads to confusion or ambiguity due to insufficient information or poorly defined concepts.

Misleading Scope:

A representation or definition of a topic, project, or idea that inaccurately defines its boundaries, objectives, or intentions. Misleading scope can result in misunderstandings, unmet expectations, or misaligned goals.

Method: In the garment industry, employees play a key role and require a thorough analysis due to their significant impact on production quality. Therefore, it is necessary to objectively evaluate the skill levels of workers, as current subjective assessment methods are limited. Three multi-criteria decision-making techniques are talked about in this article methods were carried out. The WSM, WPM, and AHP techniques were used to assess employee skill levels and improve operator selection for specific tasks. The evaluation criteria in this study are classified separated into three sections: attendance rate (AR), activity (A), and quality index (QI). [19] Many Techniques for AHP have been suggested, and WSM is widely utilized for evaluating and selecting software packages. Recently, a (HKBS) has been introduced.

However, there is no comparative analysis of HKBS with The literature on AHP and WSM techniques. As a result, this study examines and contrasts the methods for evaluating and selecting software packages include AHP, WSM, and HKBS. [20] (WSM) is a commonly used MCDM method for selecting the optimal supplier for a company, which aims to increase productivity and achieve customer satisfaction. Ensuring the timely delivery of goods in the right quantity and location depends on selecting the best supplier. In this research, the WSM method is applied across all criteria and alternatives. Known for its simplicity, WSM is a straightforward approach that is widely used in various applications, including robotic processing data. [21] The weighted sum method (WSM), also known as linear scalarization, is a technique used to transform a multi-objective optimization problem (MOP) by combining objectives using convex weights. Although WSM can provide a Pareto optimal solution under certain conditions, it has limitations.

It cannot generate solutions in non-convex Pareto front areas and can be produced duplicate solutions even with different weight combinations. In addition, it often fails to ensure an equal distribution of Pareto points. In contrast, one-step methods aim to generate all Pareto optimal solutions or a representative choice of them. These approaches are generally classified into two groups: mathematical programming-based approaches, where each algorithm run generates a single Pareto optimal solution and evolutionary algorithms, which can generate a set of Pareto optimal outcomes from a single execution. [22] In this study, both AHP and WSM methods were used to determine Optimal Factors affecting the suitability of dam sites include fourteen major components identified through a combination of remote sensing and ancillary data.

Importantly, this study introduced the use of stream width derived from high-resolution imagery it is utilized as a predictor for choosing dam locations as opposed to depending solely on conventional river discharge measurements. The reference locations were 21 dam sites that MAWR recommended. Furthermore, the precision of AHP and WSM was assessed methods. [23] When using alternative initial values for the design, gradient-based optimizers such as SQP fail to obtain optimal or reliable results. As a result, in typical RBDO problems, designers often must test multiple starting points to achieve acceptable results, although it is time-consuming and computationally demanding. In contrast The initial starting point has no effect on the suggested hybrid PSO-WSM approach, which is capable of successfully achieving an optimal design without any problems it the need for additional information. [24] (WSM) is one of the most straightforward and intuitive approaches, suitable for single-dimensional problems.

It relies on the additive utility theory, which states the total value of the alternative is its total amount its weighted criterion values. WSM is straightforward to apply when the criteria have the same unit range. However, when the criteria involve different units, such as a combination of qualitative and quantitative characteristics, this assumption is violated, complicating the process and necessitating the use of normalization techniques. Due to its simplicity, WSM is often combined with other methods, such as AHP, to increase its applicability.[25] As a result, the system is fully controlled, and any measurement errors in the frequency response can lead to Significant mistakes in the predicted band structure can result from elements like the accelerometer's and load cell's restricted size (compared to an ideal infinite point), small displacements when positioning the accelerometer precisely at a unit cell length, and manufacturing defects. Variations, can lead to differences between the experimental data and the analysis.

In addition, during the experiment, the accelerometer was repositioned at each measurement point for frequency response analysis. The mass of the accelerometer can be changed, and additional modes can be introduced. Since the accelerometer is placed in the same place during each measurement, the duration of the beam disturbed. Since the WSM assumes a finite periodic system, the added mass can introduce significant errors. This problem can be mitigated by placing identical accelerometers throughout the beam or by adopting alternative techniques. [26] The Weighted Sum Method (WSM) has proven to be very useful in applications in data processing and robotics.

It is best suited for scenarios involving single-dimensional concerns. The weights used in this method were determined using two approaches: a fuzzy analysis hierarchy process combined with a Both the Markov chain-based weighting technique and the geometric mean method are applied, with the weights multiplied by the values assigned to each criterion, the resulting products are summed across all criteria. [27] The first criterion is based on the principle that a method that can provide accurate results for Multidimensional issues must also function precisely. There is no reason why the multidimensional approach should not work in single-dimensional circumstances these cases, since they are essentially simplified versions of multidimensional problems these cases.

The weighted sum method (WSM) consistently yields higher results reliable results for most single-dimensional problems, its results are used as a benchmark to assess the effectiveness of the remaining three techniques in this context. [28] The average the value produced utilizing the laboratory approach is around 30 mm larger than the grain size estimated by image analysis following the use of DCM. This disparity is negligible in comparison to the 50 mm discrepancy between the calculated average grain sizes by laboratory measurements and image analysis utilizing WSM. The binary images processed with DCM were subjected to the Schwartz-Saltykov approach in order to address stereological effects in thin section measurements. The average diameter shifted by 10 mm in the direction of a wider size range as a result of this adjustment. [29]

This field of study can benefit from the introduction of a new methodology for simulating the rational urban areas of the future, involving a determination process designed to calibrate and validate weighting values. Furthermore, time-consuming challenges in GIS and spatial modeling research need to be overcome. Therefore, a new optimization method needs to be developed to produce more efficient and reliable results. In this regard, the goal is to develop an optimization method for determining the weight value of multiple criteria using AHP, with the aim of creating a feasible urbanization surface. [30] The WSM and CP methods incorporate criterion weights A modified epsilon-constraint (EC) The objective function approach is suggested, where the weights determined using the SWARA method are used for the hybrid, CP, and WSM methods.

Criterion weights are used in both the EC and modified EC approaches to identify the most important criterion and the objective function, respectively. All methods, except the EC method, gave comparable results in terms of optimal variance. The EC technique's ideal transportation plan was comparable to the results of individual optimizations, and the modified EC method also provided comparable outcomes WSM and CP methods in terms of optimal variance.

Analysis and Discussion

Table 1.Diagnostic Assistance Applications

	DATA SET			
	Clarity	Market Relevance	Vagueness	Misleading Scope
Full Stack Tech Lead	74.000	139.530	14.000	58.000
Software Engineering Manager	85.000	142.970	25.000	69.000
Principal Engineer – AI Solutions	96.000	122.580	34.000	45.000
Senior Solution Architect	41.000	128.280	36.000	67.000
Cloud Infrastructure Specialist	52.000	186.410	47.000	92.000

The data presented in Table 1 highlights the performance of various roles in terms of diagnostic assistance applications across four key metrics: Clarity, Market Relevance, Vagueness, and Misleading Scope. These metrics provide insight into how well each role performs in terms of delivering clear and relevant solutions while minimizing ambiguity and scope misrepresentation. Clarity is highest for the Principal Engineer – AI Solutions (96.000), indicating their strength in providing precise and easily understood outputs. Conversely, the Senior Solution Architect scores the lowest (41.000), suggesting potential challenges in communicating clear solutions. Market Relevance is led by the Cloud Infrastructure Specialist (186.410), demonstrating their alignment with current market needs. The Principal Engineer – AI Solutions (122.580) lags slightly in comparison, perhaps due to niche focus areas. Vagueness is lowest for the Full Stack Tech Lead (14.000), reflecting their ability to provide detailed and precise outputs, while the Cloud Infrastructure Specialist scores highest (47.000), indicating more room for refinement in this area. Misleading Scope is most significant for the Cloud Infrastructure Specialist (92.000), implying challenges in defining realistic project boundaries, while the Principal Engineer – AI Solutions (45.000) fares better in this regard.

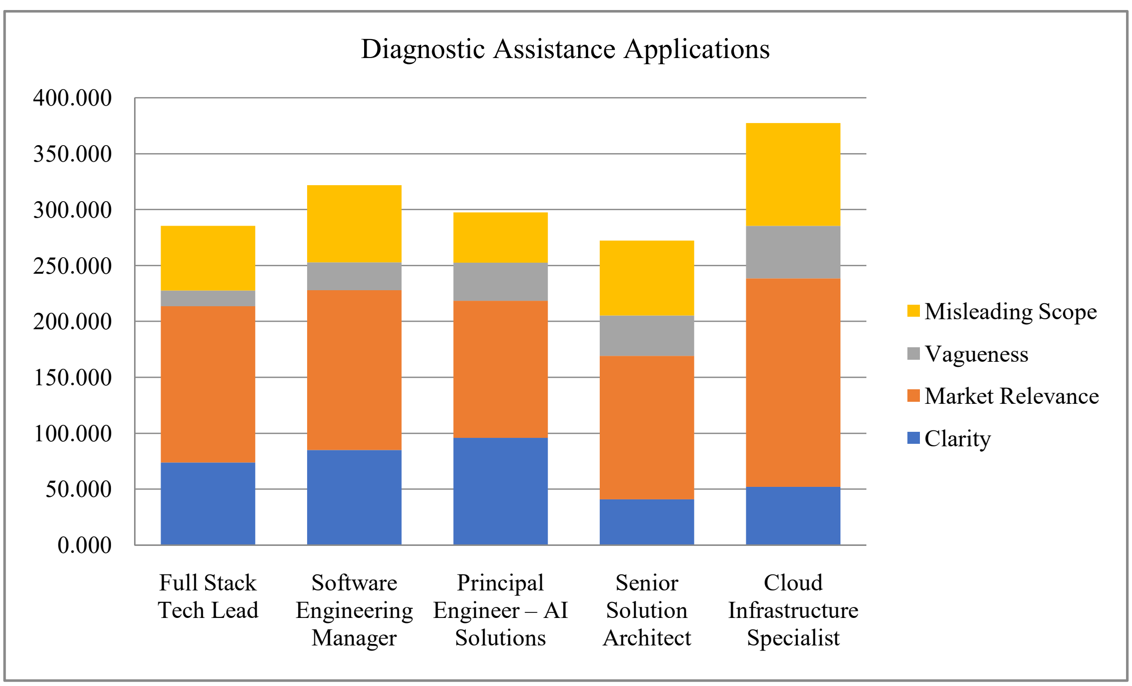

Figure 1.Diagnostic Assistance Applications

The figure 1 compares roles across four metrics: Clarity, Market Relevance, Vagueness, and Misleading Scope. The Principal Engineer – AI Solutions excels in clarity (96.000) but has moderate market relevance (122.580). In contrast, the Cloud Infrastructure Specialist leads in market relevance (186.410) but exhibits high vagueness (47.000) and misleading scope (92.000). The Full Stack Tech Lead achieves a balance with low vagueness (14.000) and strong relevance (139.530). The Software Engineering Manager combines high clarity (85.000) and relevance (142.970) but shows moderate vagueness and scope challenges. Meanwhile, the Senior Solution Architect struggles with clarity (41.000) and high vagueness (36.000).

Table 2. Normalized

	Normalized			
	Clarity	Market Relevance	Vagueness	Misleading Scope
Full Stack Tech Lead	0.77083	0.74851	1.00000	0.77586
Software Engineering Manager	0.88542	0.76697	0.56000	0.65217
Principal Engineer – AI Solutions	1.00000	0.65758	0.41176	1.00000
Senior Solution Architect	0.42708	0.68816	0.38889	0.67164
Cloud Infrastructure Specialist	0.54167	1.00000	0.29787	0.48913

Table 2 presents normalized scores for various roles based on Clarity, Market Relevance, Vagueness, and Misleading Scope, highlighting their relative performance across these dimensions. Principal Engineer – AI Solutions stands out with the highest clarity (1.00000) and excels in maintaining the least misleading scope (1.00000). However, its market relevance (0.65758) is moderate, potentially reflecting a niche focus. Cloud Infrastructure Specialist dominates in market relevance (1.00000), indicating strong alignment with industry demands, but scores lowest in vagueness (0.29787) and misleading scope (0.48913), and suggesting room for improvement in precision and scope management. Full Stack Tech Lead balances strong clarity (0.77083) and market relevance (0.74851) while achieving the best score in vagueness (1.00000), showing consistent detail and accuracy. Software Engineering Manager combines high clarity (0.88542) and good market relevance (0.76697) but struggles with vagueness (0.56000) and scope issues (0.65217). Senior Solution Architect faces challenges in clarity (0.42708), the lowest among the roles, and moderate vagueness (0.38889) but shows balanced market relevance (0.68816) and scope (0.67164). Overall, the table emphasizes each role's strengths and areas for improvement, reflecting their adaptability to diagnostic assistance applications.

Table 3.Weight

	Weight			
Full Stack Tech Lead	0.25	0.25	0.25	0.25
Software Engineering Manager	0.25	0.25	0.25	0.25
Principal Engineer – AI Solutions	0.25	0.25	0.25	0.25
Senior Solution Architect	0.25	0.25	0.25	0.25
Cloud Infrastructure Specialist	0.25	0.25	0.25	0.25

Table 3 illustrates the equal weighting (0.25) assigned to each of the four metrics Clarity, Market Relevance, Vagueness, and Misleading Scope for all roles: Full Stack Tech Lead, Software Engineering Manager, Principal Engineer AI Solutions, Senior Solution Architect, and Cloud Infrastructure Specialist. This uniform distribution of weights reflects an unbiased evaluation approach, where each metric is considered equally important in assessing the performance and suitability of a role for diagnostic assistance applications. The equal weighting suggests that no single dimension, such as clarity or market relevance, is prioritized over others, emphasizing the need for a balanced competency profile. For example, while roles like the Principal Engineer AI Solutions excel in clarity and minimal scope issues, their performance in market relevance may hold equal significance in the overall evaluation. Similarly, the Cloud Infrastructure Specialist, despite its high market relevance, would also need to address weaknesses in vagueness and scope for a balanced score. This approach highlights that success in diagnostic assistance applications depends on consistent performance across all metrics, ensuring that each role's strengths and weaknesses are given equal importance in the overall assessment and decision-making process.

Table 4. Weighted normalized decision matrix

	Weighted normalized decision matrix			
Full Stack Tech Lead	0.19271	0.18713	0.25000	0.19397
Software Engineering Manager	0.22135	0.19174	0.14000	0.16304
Principal Engineer – AI Solutions	0.25000	0.16440	0.10294	0.25000
Senior Solution Architect	0.10677	0.17204	0.09722	0.16791
Cloud Infrastructure Specialist	0.13542	0.25000	0.07447	0.12228

Table 4 presents the weighted normalized decision matrix, combining the normalized scores and equal weights for Clarity, Market Relevance, Vagueness, and Misleading Scope across five roles. This matrix provides a balanced evaluation of their overall performance in diagnostic assistance applications. Principal Engineer – AI Solutions achieves the highest score in clarity (0.25000) and minimal misleading scope (0.25000), emphasizing its ability to provide precise and well-scoped solutions. However, its lower scores in market relevance (0.16440) and vagueness (0.10294) suggest a focus on niche, rather than broadly applicable, solutions. Full Stack Tech Lead demonstrates balanced performance across all metrics, with strong clarity (0.19271), market relevance (0.18713), and minimal vagueness (0.25000), making it a versatile role. Software Engineering Manager excels in clarity (0.22135) and relevance (0.19174) but struggles with vagueness (0.14000) and misleading scope (0.16304), indicating potential challenges in precision and boundary definition. Senior Solution Architect and Cloud Infrastructure Specialist show weaker overall performance, particularly in vagueness and misleading scope. While the Cloud Infrastructure Specialist leads in market relevance (0.25000), its low scores in vagueness (0.07447) and scope (0.12228) reveal significant gaps

.

Table 5.Preference Score

	Preference Score
Full Stack Tech Lead	0.82380
Software Engineering Manager	0.71614
Principal Engineer – AI Solutions	0.76734
Senior Solution Architect	0.54394
Cloud Infrastructure Specialist	0.58217

Table 5 presents the Preference Scores for five roles in diagnostic assistance applications, which reflect the overall performance based on the weighted normalized decision matrix. The higher the preference score, the more favorable the role is in terms of its suitability for the application. Full Stack Tech Lead emerges with the highest preference score (0.82380), indicating that, overall, this role is the most balanced and well-suited for the application. It demonstrates strong performance across key metrics, including clarity, market relevance, and minimal vagueness.

Software Engineering Manager ranks second with a preference score of 0.71614. While it performs well in clarity and market relevance, it faces challenges in vagueness and misleading scope, which slightly lower its overall score.

Principal Engineer – AI Solutions scores 0.76734, showing that it performs strongly in clarity and scope but has room for improvement in market relevance and vagueness. Its specialized nature may limit its broader applicability.

Senior Solution Architect and Cloud Infrastructure Specialist score lower (0.54394 and 0.58217, respectively). These roles exhibit weaknesses, particularly in clarity and vagueness, which reduce their suitability for the application compared to the others.Overall, this table reflects how well each role aligns with the desired outcomes in diagnostic assistance applications, with the Full Stack Tech Lead leading the preference ranking.

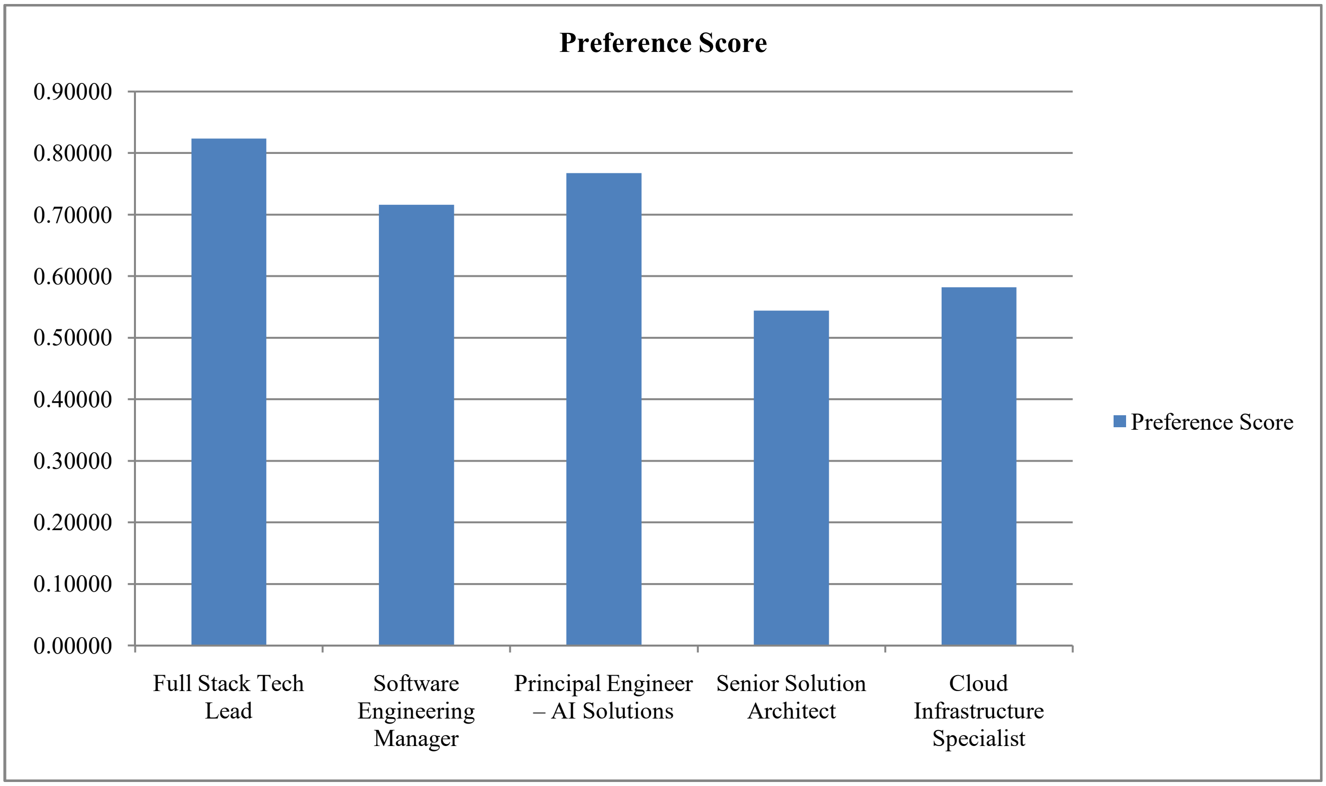

Figure 2.preference Score

Figure 2 shows the preference scores for five roles in diagnostic assistance applications, indicating their overall suitability based on various metrics. The Full Stack Tech Lead has the highest score (0.82380), reflecting its balanced performance across clarity, relevance, and minimal vagueness. The Software Engineering Manager follows with a score of 0.71614, performing well in clarity and relevance but facing challenges in vagueness. The Principal Engineer AI Solutions scores 0.76734, excelling in clarity and scope. Senior Solution Architect and Cloud Infrastructure Specialist score lower, indicating areas for improvement in clarity and vagueness.

Table 5.Rank

	Rank
Full Stack Tech Lead	1
Software Engineering Manager	3
Principal Engineer – AI Solutions	2
Senior Solution Architect	5
Cloud Infrastructure Specialist	4

Table 5 presents the ranking of five roles based on their preference scores in diagnostic assistance applications. The Full Stack Tech Lead holds the top rank (1), indicating its overall suitability for the application, supported by a strong performance across key metrics like clarity, market relevance, and minimal vagueness. This makes it the most balanced and versatile role among the group. The Principal Engineer – AI Solutions follows in second place (2), reflecting its high clarity and minimal misleading scope. However, its market relevance and vagueness scores slightly lower, which limits its broader applicability, placing it just behind the Full Stack Tech Lead. The Software Engineering Manager ranks third (3), showing solid performance in clarity and market relevance, but it faces challenges in vagueness and scope, which lower its overall suitability compared to the top two roles. The Cloud Infrastructure Specialist is ranked fourth (4), leading in market relevance but showing notable weaknesses in vagueness and misleading scope, making it less well-rounded overall. Lastly, the Senior Solution Architect is ranked fifth (5), with lower scores in clarity and vagueness, which diminishes its overall effectiveness in diagnostic assistance applications compared to the other roles. This ranking outlines each person's advantages and disadvantages role, emphasizing the Full Stack Tech Lead as the most preferable choice.

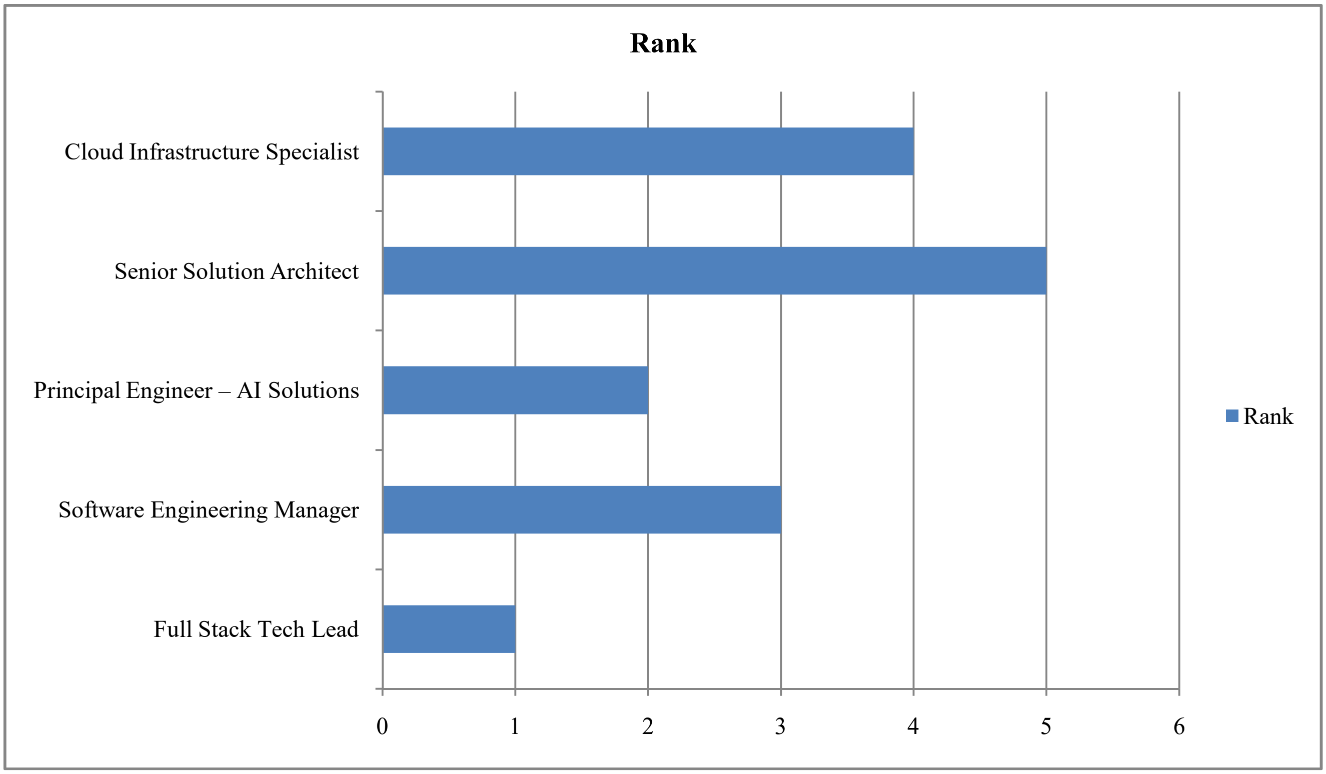

Figure 3.Rank

Figure 3 presents the rankings of five roles based on their suitability for diagnostic assistance applications. The Full Stack Tech Lead ranks first, indicating its well-rounded performance across key metrics. The Principal Engineer – AI Solutions comes second, excelling in clarity and scope but falling slightly short in market relevance and vagueness. The Software Engineering Manager ranks third, performing well in clarity and relevance but struggling with vagueness and scope. The Cloud Infrastructure Specialist ranks fourth due to strong market relevance but lower scores in vagueness and scope. The Senior Solution Architect ranks fifth, with lower clarity and vagueness scores.

Conclusion

The evolution of diagnostic systems and methodologies has significantly transformed both medical and technical fields, presenting both opportunities and challenges. Throughout this comprehensive review, several key developments and challenges have emerged in the advancement of diagnostic technologies and methodologies. In the medical domain, artificial intelligence and machine learning have shown considerable promise in improving diagnostic accuracy and efficiency. However, these technologies face important limitations, particularly in handling complex medical data and ensuring interpretability. The integration of AI-based diagnostic assistants (DAs) and expert systems has demonstrated potential in reducing healthcare costs and improving accessibility, though challenges persist in achieving consistent accuracy and seamless integration with existing healthcare workflows. Significant progress has been made in diagnostic imaging and monitoring systems, exemplified by developments in breast cancer detection and the implementation of systems like WHAM-BioS.

These advances have led to more precise and efficient diagnostic capabilities, particularly in specialized medical fields. The emergence of novel diagnostic tools, such as saliva-based testing and exosome analysis, offers promising alternatives to traditional methods, potentially making diagnostics more accessible and less invasive. In the technical sphere, the Weighted Sum Method (WSM) has emerged as a versatile tool for decision-making across various applications, from software selection to industrial diagnostics. While WSM offers advantages in simplicity and straightforward implementation, its limitations in handling multi-dimensional problems and non-convex solutions necessitate careful consideration of its application context.

The integration of diagnostic systems remains a significant challenge across sectors. Implementation issues include interoperability problems, workflow disruptions, and the need for comprehensive knowledge bases. The success of diagnostic technologies heavily depends on their ability to seamlessly integrate with existing systems and processes while maintaining high accuracy and reliability. Looking forward, the field of diagnostics continues to evolve with promising developments in areas such as multi-agent systems, deep learning approaches, and mobile diagnostic tools. However, success in these areas will require addressing current challenges in data quality, system integration, and user acceptance.

Future developments should focus on creating more robust, integrated solutions that balance technological advancement with practical implementation considerations. These findings emphasize the need of ongoing study and advancement in diagnostic methodologies, with particular attention to bridging the gap between theoretical capabilities and practical implementation. The future of diagnostic systems lies in creating more integrated, accurate, and user-friendly solutions that can effectively serve both medical and technical applications while addressing the current limitations and challenges identified in this review. The results Full Stack Tech Lead had the best ranking, and the lowest ranking was Senior Solution Architect.

Reference

1. Kumar, K. "Assistant tools for medical diagnostics through rough set-based data analysis." Indian Journal of Science and Technology 17, no. 31 (2024): 3174-3182.
2. Jones, Alicia M., and Daniel R. Jones. "A novel Bayesian general medical diagnostic assistant achieves superior accuracy with sparse history: a performance comparison of 7 online diagnostic aids and physicians." Frontiers in Artificial Intelligence 5 (2022): 727486.
3. Li, Yan, and Gaihua Li. "Tumor Diagnosis Assistant System Design Based on Data Mining Technology." In 2020 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS), pp. 824-827. IEEE, 2020.
4. Behrens, Sarah, Hendrik Laue, Matthias Althaus, Tobias Boehler, Bernd Kuemmerlen, Horst K. Hahn, and Heinz-Otto Peitgen. "Computer assistance for MR based diagnosis of breast cancer: present and future challenges." Computerized medical imaging and graphics 31, no. 4-5 (2007): 236-247.
5. Jin, Ming-Hui, Ren-Guey Lee, Cheng-Yan Kao, You-Rui Wu, D. Frank Hsu, Tse-Ping Dong, and Kuan-Tsae Huang. "Sensor network design and implementation for health telecare and diagnosis assistance applications." In 11th International Conference on Parallel and Distributed Systems (ICPADS'05), vol. 2, pp. 407-411. IEEE, 2005.
6. Gong, Wei, and Shoubin Wang. "Support vector machine for assistant clinical diagnosis of cardiac disease." In 2009 WRI Global Congress on Intelligent Systems, vol. 3, pp. 588-591. IEEE, 2009.
7. Laflamme, Lucie. "Image-based mHealth for remote diagnostic assistance a means to promote equity in quality care." Global Health Action 10, no. sup3 (2017): 1344004.
8. Mougiakakou, Stavroula G., Ioannis K. Valavanis, Nicolaos A. Mouravliansky, Alexandra Nikita, and Konstantina S. Nikita. "DIAGNOSIS: A telematics-enabled system for medical image archiving, management, and diagnosis assistance." IEEE transactions on instrumentation and measurement 58, no. 7 (2009): 2113-2120.
9. Abu-Naser, Samy S., R. Al-Dahdooh, A. Mushtaha, and M. El-Naffar. "Knowledge management in ESMDA: expert system for medical diagnostic assistance." (2010).
10. Mostafa, Salama A., MohdSharifuddin Ahmad, Mazin Abed Mohammed, and Omar Ibrahim Obaid. "Implementing an expert diagnostic assistance system for car failure and malfunction." International Journal of Computer Science Issues (IJCSI) 9, no. 2 (2012): 1.
11. Mostafa, Salama A., Aida Mustapha, Ahmed AbdulbasitHazeem, ShihabHamadKhaleefah, and Mazin Abed Mohammed. "An agent-based inference engine for efficient and reliable automated car failure diagnosis assistance." IEEE Access 6 (2018): 8322-8331.
12. Navarro Mata, Marta. "Implementation of a minority disease diagnostic assistant graphic user interface using the human phenotype ontology." Bachelor's thesis, UniversitatPolitècnica de Catalunya, 2024.
13. Kaufman, Eliaz, and Ira B. Lamster. "The diagnostic applications of saliva—a review." Critical Reviews in oral biology & medicine 13, no. 2 (2002): 197-212.
14. Jose, Sagar, Khanh TP Nguyen, Kamal Medjaher, RyadZemouri, Mélanie Lévesque, and Antoine Tahan. "Fault detection and diagnostics in the context of sparse multimodal data and expert knowledge assistance: Application to hydrogenerators." Computers in Industry 151 (2023): 103983.
15. Fang, Shimeng, HongzhuTian, Xiancheng Li, Dong Jin, Xiaojie Li, Jing Kong, Chun Yang et al. "Clinical application of a microfluidic chip for immunocapture and quantification of circulating exosomes to assist breast cancer diagnosis and molecular classification." PloS one 12, no. 4 (2017): e0175050.
16. Hossack, John A., Judith Menal, Stephen DJ McArthur, and James R. McDonald. "A multiagent architecture for protection engineering diagnostic assistance." IEEE Transactions on Power Systems 18, no. 2 (2003): 639-647.
17. Keplar, Kristine E., and Christopher J. Urbanski. "Personal digital assistant applications for the healthcare provider." Annals of Pharmacotherapy 37, no. 2 (2003): 287-296.
18. Chourabi, Zouhour, FaouziKhedher, AmelBabay, and MorchedCheikhrouhou. "Multi-criteria decision making in workforce choice using AHP, WSM and WPM." The Journal of The Textile Institute 110, no. 7 (2019): 1092-1101.
19. Jadhav, Anil, and Rajendra Sonar. "Analytic hierarchy process (AHP), weighted scoring method (WSM), and

hybrid knowledge based system (HKBS) for software selection: a comparative study." In 2009 Second International Conference on Emerging Trends in Engineering & Technology, pp. 991-997. IEEE, 2009.

20. Dwivedi, Sanjay Kumar, and AshutoshDwivedi. "Application of MOORA and WSM method for supplier selection in manufacturing." International Journal for Advance Research and Development 3, no. 7 (2018): 114-117.
21. Ghane-Kanafi, A., and E. Khorram. "A new scalarization method for finding the efficient frontier in non-convex multi-objective problems." Applied Mathematical Modelling 39, no. 23-24 (2015): 7483-7498.
22. Othman, Arsalan Ahmed, Ahmed F. Al-Maamar, Diary Ali Mohammed Amin Al-Manmi, VeraldoLiesenberg, Syed E. Hasan, Ahmed K. Obaid, and Ayad M. Fadhil Al-Quraishi. "GIS-based modeling for selection of dam sites in the Kurdistan Region, Iraq." ISPRS International Journal of Geo-Information 9, no. 4 (2020): 244.
23. SafaeianHamzehkolaei, Naser, Mahmoud Miri, and Mohsen Rashki. "An enhanced simulation-based design method coupled with meta-heuristic search algorithm for accurate reliability-based design optimization." Engineering with Computers 32 (2016): 477-495.
24. Kolios, Athanasios, VarvaraMytilinou, Estivaliz Lozano-Minguez, and KonstantinosSalonitis. "A comparative study of multiple-criteria decision-making methods under stochastic inputs." Energies 9, no. 7 (2016): 566.
25. Junyi, L., V. Ruffini, and D. Balint. "Measuring the band structures of periodic beams using the wave superposition method." Journal of Sound and Vibration 382 (2016): 158-178.
26. Abiola, Isaac Temitope, and Sunday AyoolaOke. "Fuzzy analytic hierarchy process and markov chain-WSM/WPM/WASPAS approaches to solving the surface roughness problem in the boring of carbon steel ARE 2062 GR E250 plates on CNC." Indonesian Journal of Industrial Engineering and Management 3, no. 1 (2022): 47-71.
27. Triantaphyllou, Evangelos, and Stuart H. Mann. "An examination of the effectiveness of multi-dimensional decision-making methods: A decision-making paradox." Decision support systems 5, no. 3 (1989): 303-312.
28. Van den Berg, E. H., A. G. C. A. Meesters, J. A. M. Kenter, and W. Schlager. "Automated separation of touching grains in digital images of thin sections." Computers & geosciences 28, no. 2 (2002): 179-190.
29. Kim, Dae-Sik. "Development of an optimization technique for a potential surface of spatial urban growth using deterministic modeling methodology." Journal of urban planning and development 135, no. 2 (2009): 74-85.
30. Stoilova, Svetla. "An integrated multi-criteria and multi-objective optimization approach for establishing the transport plan of intercity trains." Sustainability 12, no. 2 (2020): 687.