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Intelligent Healthcare Decisions Leveraging WASPAS for Transparent AI Applications

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Abstract

Introduction: The use application of artificial intelligence (AI) in healthcare has changed dramatically since its early exploration in diagnosing acute abdominal pain. Today, AI enhances clinical decision-making, precision medicine, and diagnostics, particularly in visually-focused specialties like radiology and dermatology. Despite its potential, widespread adoption is hindered by concerns over transparency, especially with black-box models. Explainable AI aims to address this by improving the transparency and traceability of complex machine learning models, thereby maintaining patient trust and supporting evidence-based decision-making.

Research Significance: This research is significant as it explores the way that artificial intelligence (AI) is changing medical practice, emphasizing explainable AI to enhance transparency and trust. By addressing challenges in complex clinical decision-making and advancing precision medicine, this study contributes to improved diagnostics and treatment. Additionally, it examines the ethical, educational, and regulatory aspects of AI integration, paving the way for safer and more effective healthcare applications, ultimately benefiting patient care and outcomes.

Methodology: Alternatives: Incineration, Autoclave, Encapsulation, Distillation, Ozonation.

Evaluation Parameters: Waste residues, Process complexity, financial profit, Impact on quality of life.

Result: The results show that Autoclave received the highest ranking, whereas Ozonation received the lowest ranking.

Conclusion: Autoclave has the highest value for artificial intelligence and medicine according to the WASPAS approach.

Keywords: Artificial Intelligence (AI), Explainable AI (XAI), Medical Applications, Transparency, Machine Learning.

Introduction

[1] The use of AI technology in surgery was initially explored by Gunn in 1976, who investigated the potential of using computer analysis to diagnose acute abdominal pain. Over the past twenty years, interest in medical AI has grown significantly. Contemporary medicine faces the challenge of gathering, interpreting, and utilizing vast amounts of information needed to address complex clinical issues. [2]Explainable in the world of medicine, artificial intelligence has drawn a lot of attention. The difficulty of explain ability has been present since the inception of AI, with traditional AI systems offering transparent and understandable methods. However, they struggled with managing real-world uncertainties. The rise of probabilistic learning improved the effectiveness of AI applications but also made them more opaque. Explainable AI seeks to enhance the transparency and traceability of complex statistical machine learning models, especially deep learning (DL). However, to achieve truly explainable medicine, there is a need to move beyond explainable AI and embrace causability.[3] Advancements in artificial intelligence (AI) algorithms and increased availability of training data have recently made it possible for AI to enhance or even replace certain tasks performed by physicians. However, despite growing interest from various stakeholders, the widespread use of AI in medicine remains limited. According to many experts, a major barrier to adoption is the lack of transparency in some AI algorithms, particularly black-box models. Clinical medicine, which depends on evidence-based decision-making, requires transparency. If AI systems cannot provide medically understandable explanations and physicians cannot clearly justify their decisions, patient trust may be compromised. To overcome this transparency challenge, explainable AI has been developed. [4] Medical practice is about to undergo a transformation because to artificial intelligence. It has been investigated in a number of healthcare domains, such as natural language processing, population health, and precision medicine. The use of AI to visual tasks, or computer vision, is one field that has received a lot of attention. Because of this, AI is especially pertinent to fields that rely heavily on visual cues, such as radiology, pathology, ophthalmology, and dermatology. Large-scale digital datasets are a major factor in the development of AI since they teach deep learning algorithms how to carry out tasks like identifying lesions in medical images.[5] Medical artificial intelligence focuses on developing AI systems that assist with diagnosing conditions and suggesting treatment options. In contrast to medical applications that rely solely on statistical or probabilistic methods, medical AI uses symbolic models that represent disease entities and their connections to patient characteristics and clinical symptoms.[6] Advancements in machine learning techniques within artificial intelligence (AI) are transforming medical practice.

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Combined with rapid progress in computing power, In a variety of medical specialties, these AI-powered solutions are improving diagnosis and treatment efficiency and accuracy. Some experts believe that AI may eventually replace radiologists due to the increasing use of AI in this field. This begs the question of whether doctors in particular specialties may eventually be replaced by AI or simply enhance their capabilities without fully replacing them.[7] AI plus leverages the advancements and technologies of artificial intelligence (AI) by integrating them with conventional sectors, resulting in increased growth, innovation, and productivity. According to research, the output-to-input ratio of artificial intelligence in the medical field is better than in other industries. Significant breakthroughs are being driven by the transformation of the traditional medical model brought about by the integration of AI with medicine. AI plus medicine has attracted a lot of attention because of its exciting potential and potential influence in the future. The goal of this paper is to review the most recent uses of AI and medicine during the last several years. [8] However, completely excluding reimbursement for AI is unlikely to be practical for all AI devices. Offering separate reimbursement for AI from payers has its benefits. Notably, as seen with telemedicine, insufficient reimbursement during the early stages of AI could hinder the adoption of technology that ultimately enhances patient outcomes and reduces costs over time. Moreover, the value of AI devices may extend beyond cost savings or increased revenue for healthcare systems. For instance, AI tools can assist clinicians by organizing patient records and emphasizing important clinical information. [9] AI analytics play a crucial role in advancing precision medicine, particularly in managing chronic diseases that involve multiple organs, unpredictable acute episodes, and long progression periods. Diabetic retinopathy is one of the most severe complications affecting over 29 million Americans with diabetes. In a study Two deep learning algorithms were trained to identify and evaluate macular edema and diabetic retinopathy using 128,175 retinal pictures from 5,871 adults. These methods outperformed 54 ophthalmologists and senior residents in detecting moderately severe retinopathy and retinal edema, exhibiting high specificities (98%) and sensitivities (87%-90%). [10] Since AIME was established three decades ago, there have been significant transformations in biomedicine and healthcare, along with groundbreaking advancements in information technology.

Clinical decision-making now heavily relies on clinical practice guidelines and evidence-based medicine. Meanwhile, the healthcare system is facing significant challenges due to the rising expenses of healthcare and the growing frequency of chronic diseases. Technological progress has led to computers that are smaller, faster, more connected, and have greater storage capacity than those of 30 years ago. Additionally, high-throughput sequencing techniques have opened up new possibilities for gathering biological data. These developments are reflected in the evolving research topics presented at AIME conferences over the years. [11] AI solutions in healthcare are distinct from medications or medical equipment as their purpose is to affect human judgment. The usefulness of the data they provide depends on how users perceive, understand, and act on it. Therefore, evaluating the impact of AI in medicine requires considering its target audience. The Food and Drug Administration (FDA) offers broad principles for regulating AI and machine learning applications, but it doesn't provide specific guidance on how to do each evaluation stage. [12] In this paper, the discussion of medical disclosure related to AI will cover not only informed consent but also the broader duty to provide patients with relevant information.

However, since the most significant AI applications in medicine are associated with procedures that require informed consent, the primary focus will remain on disclosure within that context. With this understanding of the importance of medical disclosure, I will now explore the topic in more depth. Typically, medical disclosure involves informing patients regarding a medical procedure or course of action's risks, advantages, and other alternatives. [13] Artificial intelligence having the capacity to increase productivity at work and support clinical decision-making in medicine. To ensure the safe use of AI applications, clinicians must have a basic understanding of AI. Although many experts recommend educating medical professionals about AI concepts, Few formal programs, particularly at the national level, have been extensively implemented in areas like model interpretation and validation techniques comprehension. According to Pinto Dos Santos et al.'s survey, 71% of 263 medical students expressed a need for AI training. Designing AI education for medical professionals requires a careful balance between technical and non-technical topics, considering the diverse backgrounds of learners. This paper shares insights from presenting three sets of medical students with an AI workshop series and making suggestions for further AI education in medicine.[14] This editorial examines the historical milestones and current advancements of AI, with a focus on large language models, highlighting the need for thorough clinical evaluation.

It emphasizes that AI in medicine must be subjected to the same rigorous Despite the difficulties brought on by its intricacy; it is examined as any clinical intervention, mostly through randomized controlled trials. In the future, NEJM AI hopes to advance interdisciplinary discussion and support an open, patient-centered strategy for AI in healthcare. It emphasizes how crucial it is to use accessible and varied datasets. The editorial envisions NEJM AI not only as a source of information but also as a key player in ethically integrating AI into healthcare while maintaining patient autonomy and the highest standards of care.[15] This essay seeks to persuasively argue for the significance of filling in the gaps in AI software's explained ability and its outcomes for users. To achieve this, the paper introduces a well-developed conceptual model for understanding explainable AI (XAI), thoroughly reviews existing research, identifies gaps in both research and practical applications of XAI, and suggests ways to bridge these gaps. Although many of the definitions and concepts discussed are broadly applicable across various fields, the paper focuses specifically on XAI in Health and Medicine. These regions have particular needs that make explain ability particularly challenging and deserving of special consideration.

Materials and Method

Alternatives:

Incineration: burning the organic elements in waste materials to produce heat, flue gas, and ash as part of the waste treatment process.

Autoclave: A pressurized device that uses steam and high temperature to sterilize medical waste or other hazardous materials, rendering them safe for disposal.

Encapsulation: A method of waste disposal where hazardous waste is enclosed in a stable, solid material (like cement) to prevent the release of contaminants into the environment.

Distillation: A separation process that uses heat to vaporize a liquid, which is then condensed back into a purified form. It is often used to recycle solvents and separate chemical mixtures.

Organization: A water and air treatment process that uses ozone gas to disinfect, deodorize, and break down pollutants, effectively neutralizing contaminants.

Evaluation Parameter:

Waste Residues: The leftover materials or byproducts that remain after waste processing or treatment, which may still require further disposal or management.

Process Complexity: The degree of difficulty or intricacy involved in the steps, technologies, and operations required carrying out a particular process or activity.

Financial Profit: The monetary gain obtained from a business activity after subtracting the costs of production, operation, and other expenses from the total revenue.

Impact on Quality of Life: The effect that a process, product, or activity has on the well-being, health, comfort, and overall satisfaction of individuals or communities.

Method: Distributing various types of goods is one of the primary needs of these companies. Experts involved in the selection process often face a significant amount of imprecise, ambiguous, and uncertain information. For optimality, the WASPAS technique uses a composite scale depending on the factors that were looked for. The weighted average success criterion, or WSM technique, is the first criterion of optimality. It is a well-known and widely used MCDM strategy that is built on a number of decision criteria used to assess alternatives. Eight manufacturing decision-making problems make up the weighted aggregate product assessment (WASPAS) approach, which is a helpful MCDM tool when its solutions are examined Cutting fluid, arc welding process, industrial robot, electroplating system, forging stage, grinding stage, and material mach inability [16]. Uncertainty often emerges in the healthcare worker removal process due to various limitations, insufficient knowledge, subjective human judgment, and the inherent unpredictability of the issue. Numerous real-world multi-criteria decision-making situations have seen considerable application of fuzzy set theory, showcasing its potent capacity to manage ambiguous and uncertain data. In order to enhance FSs, Formation fuzzy sets have been proven to be an effective tool for modeling imprecision and uncertainty encountered in real-world applications [17]. Traditional cutting methods for heavy and machined metals often lack the required capacity and precision. They do not offer the same benefits as abrasive water jet and pulsed water jet cutting techniques. High-pressure water jet cutting is quickly becoming one of the most advanced manufacturing technologies.

While providing precise cuts or processing in unique conditions [18]. The ambiguity set approach is extended by Zadeh's proposed WASPAS formal, ordered fuzzy using numbers (OFNS). The OFNS concept is presented. Arithmetic functions of real numbers in this approach are ambiguous as opposed to numbers, making them a special instance of OFNS. The WASPAS method was developed using zavadskas, turskis, and an tuch eviciene. The accuracy of the WASPAS technique is a weighted quantity as opposed to a method that is employed or a weighted product model that is suggested. The idea lacks unified investigation, and the current literature's attempt to examine OFNS in ambiguous WASPAS mode failed. [19]. Despite serving a vast market, the industry is highly competitive with many service providers competing for market share. For any service provider to stay in business, it is essential to provide reliable, high-quality services to customers, while minimizing costs [20]. The quest for sustainable urban development has become a global goal, leading to a reassessment of urban dynamics and inspiring diverse thinking. At the heart of this conceptual study are three main pillars: environmental, social, and economic. Faced with multiple pressures and expectations, cities need to reorganize the complex relationships between residents, ecology, economy, society and politics [21]. Weighted Total Product Assessment (WASPAS), a time-based application of the software, is integrated into the problem. The critical approach is a goal to find a quantitative weighting method, which includes the depth of the selection and version A contradiction is maintained inside the problem's structure.

The approach is based on the Weighted Sum Version (WSM) and the Weighted Product Model (WPM), and it falls under the elegance of conversational methods and alternatives. The information on the standards to be evaluated is mostly based on WASPAS. Both the composition and the ranking options are rich. This article's new foundation for the literature is criticism and WASPAS. The primary factor that has contributed to this is evidence. [22]. this demonstrates that individuals are constantly looking for ways to generate income using information available on the internet. Search trends indicate that people are engaging in three distinct methods or trades, such as holding stocks or crypto currencies. This suggests that individuals are exploring various investment options for their capital. However, for those of Islamic faith, some of these options may not be in line with religious principles, as activities such as interest or usury, or holding shares in companies that sell alcohol, are considered sinful [23]. Most previous studies on these topics have focused on individual aspects of quality of service, such as the time required to complete workflows, which are commonly considered in many MacBun instances. As a result, an effective task-scheduling algorithm must balance multiple objectives related to quality of service [24]. A new method based on the WASPAS approach is developed with HFS. Various information for calculating the experts and Actions using scale weights are suggested. The HF-operators, scalar weight estimate approach, and WASPAS technique are modified.

The developed method is implemented for the inexperienced dealer selection problem. HFSS for estimating MCDM problems with a unified method based on WASPAS method and information functions [25]. As digital transformation and digitization continue to expand, the evolution of concepts, It has become essential to produce smart products and services, physical and digital systems, and creative business strategies. Digitization demands significant, wide-ranging changes in various aspects, including business models, operations, and organizational culture, With improvements in multiple areas of the business to unlock the company's full potential, such as personalization, performance, and security [26]. Public transportation is a service accessible to the public, serving as a fundamental need and a vital component of city life. Recent developments in transport technology have seen an increase in online-based public transport options [27]. As technology advances and the population grow, society and businesses are increasingly dependent on energy to support their daily activities. This increasing demand for energy has increased the importance of businesses operating in this sector. As a result, it is essential to address these needs by utilizing various energy sources, and today electrical energy is the most common and important of these sources [28]. Thepresent study uses the Product Evaluation (if-WASPAS) technique to examine the performance of the TSPS Intuitive Fuzzy Weighted Aggregator for Comparison. The suggested approach involves calculating a new method based on the highly measured weights of IFSS operators, integrating subjective weights, measuring the outcomes with expert-expressed weights, and using more acceptable weights resulting from similarity to achieve objectivity. [29].

Result and Discussion

Table 1. Artificial intelligence and medicine

	Artificial intelligence and medicine			
	Waste residues	Process complexity	Financial profit	Impact on quality of life
Incineration	159.00000	856.00000	80.70000	8.00000
Autoclave	126.00000	347.97000	56.70000	9.00000
Encapsulation	257.00000	386.58000	89.40000	7.00000
Distillation	357.00000	388.28000	100.00000	3.00000
Ozonation	951.00000	968.41000	92.30000	5.00000

Table 1 presents an analysis of various waste treatment methods in the context of artificial intelligence and medicine, evaluating them based on four key parameters: waste residues, process complexity, financial profit, and impact on quality of life. Incineration shows moderate waste residues (159.00) and high process complexity (856.00), with financial profit (80.70) and a relatively low impact on quality of life (8.00). This suggests that while incineration is complex and profitable, it has environmental and societal drawbacks. Autoclave methods exhibit lower waste residues (126.00) and reduced process complexity (347.97), with moderate financial profit (56.70) and a slightly better impact on quality of life (9.00). This indicates a more balanced approach but with limited profitability. Encapsulation leads to higher waste residues (257.00) and moderate complexity (386.58), offering good financial profit (89.40) but a lower impact on quality of life (7.00), possibly due to environmental concerns.

Distillation generates the highest financial profit (100.00) but also involves significant waste residues (357.00) and complexity (388.28), with a poor impact on quality of life (3.00). Ozonation shows the highest waste residues (951.00) and complexity (968.41), with substantial financial profit (92.30) but a low impact on quality of life (5.00), indicating environmental and health implications.

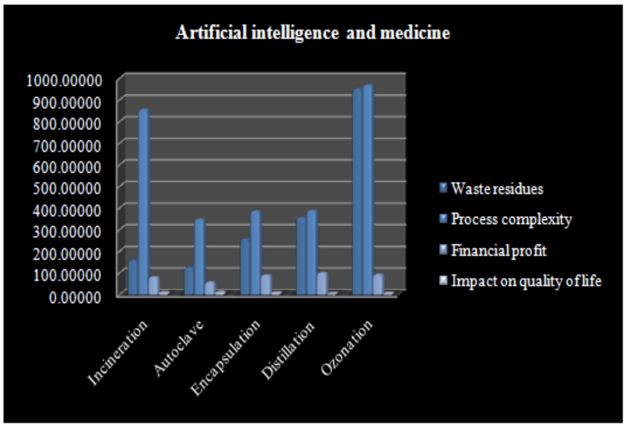

Figure 1: Provides a comparative analysis of different waste treatment methods

Figure 1 provides a comparative analysis of different waste treatment methods in the context of artificial intelligence and medicine, using four key parameters: waste residues, process complexity, financial profit, and impact on quality of life. Incineration produces moderate waste residues (159.00) and has high process complexity (856.00). It generates considerable financial profit (80.70) but has a lower impact on quality of life (8.00), possibly due to environmental pollution. Autoclave demonstrates the lowest waste residues (126.00) and relatively low process complexity (347.97), but it also has the lowest financial profit (56.70). However, it achieves the highest impact on quality of life (9.00), suggesting it is more environmentally friendly. Encapsulation shows higher waste residues (257.00) with moderate complexity (386.58) and a good financial profit (89.40). However, it has a lower impact on quality of life (7.00), likely due to environmental containment concerns. Distillation yields the highest financial profit (100.00) but also high waste residues (357.00) and process complexity (388.28). It has the lowest impact on quality of life (3.00), indicating potential environmental and health risks. Ozonation results in the highest waste residues (951.00) and complexity (968.41), with high financial profit (92.30) but a poor impact on quality of life (5.00), reflecting significant environmental challenges.

Table 2: Presents the performance values of five waste treatment methods Incineration, Autoclave, Encapsulation, Distillation

	Performance value			
Incineration	0.1671924	0.883923	0.702602	0.375
Autoclave	0.1324921	0.359321	1	0.33333
Encapsulation	0.2702419	0.39919	0.634228	0.42857
Distillation	0.3753943	0.400946	0.567	1
Ozonation	1	1	0.614301	0.6

Table 2 presents the performance values of five waste treatment methods Incineration, Autoclave, Encapsulation, Distillation, and Ozonation evaluated across four criteria: waste residues, process complexity, financial profit, and impact on quality of life. Each value is normalized between 0 and 1, with higher values indicating better performance. Incineration shows a high performance in process complexity (0.883923) and financial profit (0.702602) but scores lower in waste residues (0.1671924) and impact on quality of life (0.375). This suggests that while it is economically beneficial, its environmental and social impact is less favorable. Autoclave has the lowest values for waste residues (0.1324921) and process complexity (0.359321) but achieves the highest value in financial profit (1), indicating cost-efficiency. Its moderate score in quality of life (0.33333) suggests balanced but limited social benefits. Encapsulation performs well in waste residues (0.2702419) and impact on quality of life (0.42857) but has moderate scores for process complexity (0.39919) and financial profit (0.634228).Distillation excels in impact on quality of life (1) but shows moderate values in the other categories, highlighting its potential for health and environmental benefits. Ozonation achieves the highest performance in waste residues (1) and process complexity (1), indicating maximum efficiency in these areas, but has moderate values in financial profit (0.614301) and quality of life (0.6), reflecting environmental challenges despite economic viability.

Table 3 : presents the weight distribution for five waste treatment methods

	Weight			
Incineration	0.25	0.25	0.25	0.25
Autoclave	0.25	0.25	0.25	0.25
Encapsulation	0.25	0.25	0.25	0.25
Distillation	0.25	0.25	0.25	0.25
Ozonation	0.25	0.25	0.25	0.25

Table 3 presents the weight distribution for five waste treatment methods: Incineration, Autoclave, Encapsulation, Distillation, and Ozonation. Each method is assigned equal weights of 0.25 across four evaluation criteria. This uniform distribution suggests that no single method is considered superior in any specific criterion, indicating a neutral or balanced approach to evaluation. It reflects an unbiased comparison framework, ensuring that all methods are judged on equal footing. This could be due to the desire to evaluate each method's overall performance without favoring any particular technology. The equal weighting might also imply that the criteria used are equally important in the decision-making process. This balanced approach ensures that the final ranking or evaluation is fair and comprehensive. By assigning equal weights, the analysis avoids skewed results that could arise from emphasizing one criterion over others. This methodology is particularly useful when the criteria are considered equally critical or when the decision-makers aim to provide an impartial assessment of the waste treatment methods.

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Table 4: Evaluates five waste treatment methods				
	Weighted normalized decision matrix (WSM)			
Incineration	0.0417981	0.2209808	0.1756506	0.09375
Autoclave	0.033123	0.0898302	0.25	0.0833333
Encapsulation	0.0675605	0.0997976	0.158557	0.1071429
Distillation	0.0938486	0.1002365	0.14175	0.25
Ozonation	0.25	0.25	0.1535753	0.15

The weighted normalized decision matrix (WSM) presented in Table 4 evaluates five waste treatment methods: Incineration, Autoclave, Encapsulation, Distillation, and Ozonation. The matrix uses normalized values to compare these methods across four criteria. Each value represents the weighted performance of a method in relation to a specific criterion, with higher values indicating better performance. Incineration scores moderately across all criteria, with its highest value (0.2209808) suggesting a relatively strong performance in the second criterion. Autoclave shows a peak value of 0.25, indicating excellent performance in the third criterion but lower values elsewhere, suggesting limited effectiveness across other factors. Encapsulation performs consistently but without any standout values, highlighting a balanced but moderate efficiency. Distillation excels in the fourth criterion (0.25) but is average in other areas. Finally, Ozonation demonstrates the highest scores in the first two criteria (both 0.25), reflecting superior effectiveness in these aspects.

Table 5: Presents the weighted normalized decision matrix (WPM) for evaluating five waste treatment methods				
	Weighted normalized decision matrix(WPM)			
Incineration	0.6394464	0.9696246	0.9155401	0.7825423
Autoclave	0.6033197	0.7742311	1	0.7598357
Encapsulation	0.7210048	0.794868	0.8924037	0.8091067
Distillation	0.7827479	0.7957405	0.8677523	1
Ozonation	1	1	0.8853099	0.8801117

Table 5 presents the weighted normalized decision matrix (WPM) for evaluating five waste treatment methods: Incineration, Autoclave, Encapsulation, Distillation, and Ozonation. Each value reflects the weighted performance of a method relative to a specific criterion, with values closer to 1 indicating superior performance. Incineration shows strong performance across all criteria, with its highest value (0.9696246) in the second criterion, indicating high efficiency in that aspect. Autoclave achieves a perfect score (1) in the third criterion, but its performance is relatively lower in the other categories. Encapsulation displays consistent and balanced values, with no extreme highs or lows, suggesting moderate effectiveness overall. Distillation stands out in the fourth criterion with a perfect score (1), indicating optimal performance in that area, and maintains relatively high values in the other criteria. Ozonation performs exceptionally well, scoring the highest in the first two criteria (both 1) and maintaining competitive values in the others, making it the most consistently effective option.

Table 6: Displays the preference scores calculated using two methods		
	Preference Score(WSM)	Preference Score(WPM)
Incineration	0.53218	0.44421475
Autoclave	0.45629	0.354926011
Encapsulation	0.43306	0.413809417
Distillation	0.58584	0.540491824
Ozonation	0.80358	0.779171667

Table 6 displays the preference scores calculated using two methods: Weighted Sum Model (WSM) and Weighted Product Model (WPM), for five waste treatment methods: Incineration, Autoclave, Encapsulation, Distillation, and Ozonation. Higher scores indicate better overall performance. According to WSM, Ozonation ranks the highest with a score of 0.80358, suggesting it is the most effective and preferred method across all criteria. Distillation follows with 0.58584, showing strong performance but not as balanced as Ozonation. Incineration scores moderately (0.53218), indicating competitive but not outstanding effectiveness. Autoclave and Encapsulation have the lowest scores, with Autoclave slightly ahead, reflecting limited overall efficiency. Using WPM, the ranking is consistent with WSM. Ozonation again leads with 0.779171667, maintaining its position as the top choice due to consistent high performance. Distillation remains the second most effective option with 0.540491824. Incineration performs moderately (0.44421475), while Encapsulation and Autoclave have the lowest scores, confirming their relatively weaker performance.

Table 7: Presents the WASPAS Coefficient for five waste treatment methods	
	WASPAS Coefficient
Incineration	0.4881971
Autoclave	0.4056063
Encapsulation	0.4234337
Distillation	0.5631634
Ozonation	0.7913735
lambda	0.5

Table 7 presents the WASPAS Coefficient for five waste treatment methods: Incineration, Autoclave, Encapsulation, Distillation, and Ozonation, with a lambda value of 0.5. The WASPAS method combines the Weighted Sum Model (WSM) and Weighted Product Model (WPM) to calculate a composite score, where higher values indicate better overall performance. Ozonation achieves the highest coefficient (0.7913735), confirming its status as the most effective and preferred method across all evaluated criteria. Its consistently superior performance highlights its balanced efficiency and adaptability. Distillation ranks second with a coefficient of 0.5631634, demonstrating strong performance, particularly in specific criteria, but not as balanced as Ozonation. Incineration follows with a moderate score (0.4881971), reflecting competitive but not exceptional effectiveness. Encapsulation and Autoclave have the lowest coefficients, at 0.4234337 and 0.4056063, respectively, indicating relatively weaker performance across the evaluated criteria. Autoclave ranks last, showing the least overall effectiveness compared to the other methods.

Table 8: Presents the ranking of five waste treatment methods based on their effectiveness	
	RANK
Incineration	3
Autoclave	5
Encapsulation	4
Distillation	2
Ozonation	1

Table 8 presents the ranking of five waste treatment methods based on their effectiveness or other evaluative criteria. Ozonation is ranked first, suggesting it is the most effective or preferred method among the options listed. This could be due to its strong oxidative properties, which efficiently neutralize contaminants. Distillation is placed second, likely for its ability to separate and purify chemical substances, making it suitable for specific waste types. Incineration ranks third, indicating its effectiveness in

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volume reduction and energy recovery, though it may have environmental concerns related to emissions. Encapsulation follows at fourth place, possibly due to its use in safely containing hazardous materials, albeit without neutralizing them. Autoclave holds the fifth position, suggesting it is the least preferred among these methods, potentially due to limitations in waste type compatibility or lower efficiency in pathogen destruction compared to other technologies. This ranking provides valuable insights into the comparative effectiveness or acceptability of these waste treatment techniques.

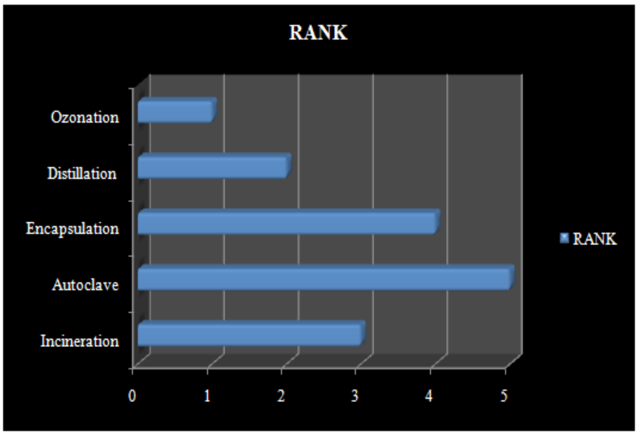

Figure 2: Shows the ranking of five waste treatment methods based on their effectiveness

Figure 2 shows the ranking of five waste treatment methods based on their effectiveness, safety, or other evaluation criteria. Ozonation is ranked first, indicating it is the most effective or preferred option. This is likely due to its strong oxidative power, which effectively breaks down pollutants and pathogens without generating harmful residues. Distillation comes in second, suggesting its high efficiency in separating and purifying chemicals, making it suitable for recycling and waste minimization. Incineration is ranked third, reflecting its effectiveness in reducing waste volume and generating energy. However, concerns about air pollution and toxic emissions might have affected its ranking. Encapsulation is placed fourth, showing its effectiveness in containing hazardous waste safely, although it doesn't neutralize the waste's harmful components. Autoclave ranks fifth, making it the least preferred method among these options. This might be due to its limitations in treating certain types of waste or lower effectiveness in complete sterilization compared to other methods. Overall, the ranking in Figure 2 provides valuable insights into the relative advantages and limitations of each waste treatment technology.

Conclusion

The integration of Medical applications of artificial intelligence (AI) have advanced dramatically since its initial exploration by Gunn in 1976, where it was first proposed as a tool for diagnosing acute abdominal pain. Over the past two decades, the interest in medical AI has surged, driven by the need to manage vast amounts of clinical data and solve complex medical problems. As medical practice becomes increasingly data-driven, AI systems offer a viable way to improve patient outcomes by increasing diagnostic precision and streamlining treatment regimens. But the growing complexity of AI models, especially deep learning algorithms, has introduced challenges related to transparency and explains ability. Traditional AI systems were more transparent but struggled with real-world uncertainties. In contrast, modern probabilistic learning models, while highly effective, are often ambiguous and challenging to understand. Explainable AI (XAI) has emerged as a result, with the goal of enhance the transparency and traceability of complex models, addressing a crucial barrier to AI adoption in clinical settings. However, for AI to be truly useful in medicine, it must go beyond explain ability and embrace causability, enabling physicians to understand not just how but also why decisions are made. Despite its transformative potential, AI adoption in clinical medicine remains limited due to concerns about transparency and trust. Black-box models, which lack clear explanations, challenge the evidence-based decision-making process fundamental to clinical practice. If physicians cannot justify AI-driven decisions in a medically understandable way, patient trust may be compromised. This underscores the importance of developing XAI systems that provide intuitive and medically relevant explanations.

AI has shown significant potential in visually-oriented medical specialties, including radiology, pathology, ophthalmology, and dermatology, leveraging advancements in computer vision and the availability of extensive digital datasets. Additionally, AI-driven systems are enhancing diagnostic accuracy and efficiency across multiple medical fields, suggesting that AI could either supplement or, in some cases, replace human specialists. However, the question remains whether AI will fully replace physicians or augment their capabilities, enhancing decision-making without completely removing the human element.Looking forward, the integration of AI with traditional healthcare practices, termed "AI plus," is expected to transform the medical model, driving productivity, innovation, and growth. To fully realize this potential, ongoing research must address current gaps in explainability, regulatory standards, and ethical considerations, ensuring that AI systems are transparent, trustworthy, and capable of enhancing quality of care while maintaining patient autonomy.

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