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Grey Relational Analysis for Expert Systems: Ranking and Performance Evaluation across Multiple Criteria

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Abstract: *This study evaluates different types of expert systems using Grey Relational Analysis (GRA) on four important criteria: functional evaluation, usability evaluation, knowledge base evaluation, and performance metrics. The research analyses five distinct expert system types: Knowledge-based systems, decision support systems, rule-based systems, intelligence systems, and logic-based systems. The method uses GRA to normalize data, calculate deviation ranks, determine Grey correlation coefficients, and establish final rankings through Grey Relational Grade (GRG). The results indicate that intelligence systems exhibit the best overall performance with the highest GRG (0.8451), especially achieving the best scores (1.0000) in functional evaluation and performance metrics. Decision support systems, which show strong performance in knowledge base evaluation, ranked second (GRG: 0.5514). With GRGs of 0.5124 and 0.4767, Knowledge-based systems and rule-based systems are in fourth and fifth place, respectively. The analysis reveals that successful expert systems require balanced performance across all evaluation criteria, rather than excelling in isolated areas. These findings provide valuable insights for organizations selecting expert systems and highlight areas for potential improvement across different system types. Incorporating the adaptive and learning capabilities demonstrated by intelligent systems may be critical for future expert system development, while the study concludes that traditional rule-based approaches may need to evolve to meet contemporary demands.*

Keywords: *Decision support systems, knowledge-based systems, intelligent systems, performance evaluation, computer ranking, artificial intelligence, computer application and operational evaluation*.

1. INTRODUCTION

The main concept of expert systems is that expertise consists of a substantial body of task-specific knowledge that is transferred from a human expert to a computer. This knowledge is stored in the computer so that users can get appropriate advice as needed. The computer can analyse a situation, make assumptions, and come to specific conclusions. Like a human advisor, it provides recommendations and, when necessary, explains the reasoning behind them. ES uses robust and versatile approaches to solve challenging problems that are encountered using traditional or conventional methods [1]. Building traditional expert systems and acquiring relevant knowledge by mimicking the reasoning methods of experts is a complex and demanding process. In contrast, building a neural network relies primarily on the availability of examples, which simplifies the construction phase and gives neural networks an edge at this stage. However, the limited ability for interpretation makes neural networks less transparent and difficult to interpret compared to conventional expert systems. Unlike traditional expert systems, convolutional expert systems achieve automated knowledge extraction from a dataset, often using feed forward-trained neural networks. By combining the reasoning capabilities of classical expert systems with the generalization and handling of incomplete information provided by neural network-based expert systems, neural fuzzy expert systems, or coarse-grained neural expert systems, hybrid expert system architectures can be built [2]. Expert systems are computer programs that originate from the field of artificial intelligence (AI), a branch of computer science research. The primary goal of AI is to understand intelligence by creating software capable of exhibiting intelligent behaviour. AI focuses on simulating reasoning and inference, to simulate human-like feelings and attitudes in a machine. The ability to make these inferences through the integration of knowledge is embedded within the system. AI programs designed to achieve expert-level Problem-solving skills in a specific domain are often knowledge-based or domain-specific expert systems. "Expert system" generally refers to a program that uses knowledge obtained directly from human experts, rather than information obtained from books or other non-human entities. In addition, the terms "expert systems", "rule-based systems", and "knowledge-based systems" are often used interchangeably [3]. Recent advances in artificial intelligence have led to the development of expert systems (ES), which are now used to a limited extent in decision-making processes. The use of both decision support systems (DSS) and ES in business decision-making is expected to grow significantly. While both systems aim to improve decision-making, they exhibit significant and distinct differences. This discussion will explore the similarities and differences between DSS and ES. Decision Support Systems (DSS) do not directly provide solutions to structured problems. Instead, they focus on providing direct support to decision-makers, helping them refine the professional judgments needed for effective decision-making. For a DSS to be truly effective, a collaborative relationship between users and the computer is essential [4]. The production system was effective in representing comprehensive information related to Diagnosis and treatment of bacterial infections. When used as designed, MYCIN outperformed medical students, interns, and physicians in training, achieving performance levels comparable to experts in bacterial diseases. However, MYCIN has not yet been implemented for widespread use. When the appropriateness of selling MYCIN cassettes to physicians for use on their microcomputers was questioned, experts in the field expressed a variety of opinions, citing a variety of reasons [5]. Problem solving is the process of finding a solution when the path to it is not clear. Although many problem-solving techniques are available, in practical situations, a single technique is often not sufficient to solve a wide range of problems. For some complex problems, there is no straightforward solution technique. In such cases, heuristic methods may be the only viable option. A heuristic is a versatile and effective strategy that can often be distilled into a single approach; however, it does not guarantee the optimal solution [6]. Proving that an expert system (ES) is ‘correct’ is a critical task. A faulty system can lead to costly errors or fail to meet expectations. In such cases, The computer's outputs may be inaccurate or irrelevant, and reliance on this may result in significant harm to the user or computer owner, such as financial loss or human suffering. For example, the implementation of professional medical diagnostic systems and income tax systems has faced challenges due to concerns about the liabilities associated with the system’s diagnostics [7]. Expert systems must communicate with humans using natural language, operate effectively even when data is flawed or judgment rules are uncertain, evaluate multiple competing hypotheses simultaneously, and provide explanations for requesting additional information when needed. In general, modern expert systems do not have advanced learning capabilities beyond basic understanding. Improving learning capabilities and incorporating them into expert system designs is an ongoing area of research [8]. Expert systems are a product of artificial intelligence that are designed to solve problems in various domains using expert-level knowledge. Successful implementations of expert systems include emerging areas such as classification and fuzzy systems, multi-agent systems, data mining, and meta-heuristic engines. As mentioned, gaining a deeper understanding of how natural cognitive processes can be effectively integrated with processes in artificial cognitive systems within a cognitive framework is critical to the development of CogInfoCom [9]. These studies indicate that users sometimes make judgments about expert system advice without fully considering the substance of the argument. Users do not always accept expert system recommendations after fully evaluating them. This idea is reinforced by the extension model, which proposes that people are less motivated to critically evaluate the content of the message and are more likely to rely on external cues when they cannot evaluate the advice on its basis [10]. The convergence of technologies in the fields of the Internet and expert systems has created new opportunities for sharing and distributing knowledge. However, there is a significant gap in research on web-based expert systems (ES). This article examines the design, development, and use of web-based ES, focusing on the benefits and challenges of developing and using them. It revisits the original theories and concepts of traditional ES and reviews the knowledge engineering framework used to build them [11]. Traditional expert systems provide decision support by following the recommendations of experts. They manage uncertainty using methods that do not rely on decision theory. These systems are valuable because they provide essential information to non-experts facing complex decisions and provide reminders to users who are stressed or fatigued. However, they also have a tendency to repeat the mistakes made by experts. This article explores the importance of effectively managing uncertainty in the Diagnosis of lymphatic diseases. This includes our research on uncertainty rationality paradigms inspired by the development of Pathfinder. In particular, we focus on the practical challenges of early decision-theoretic methods for reasoning under uncertainty and our initial attempts to address these limitations. By using non-decision-theoretic reasoning paradigms [12]. Expert systems are computer programs designed to reflect knowledge and experience domain experts in order to solve complex problems. They can acquire knowledge from experts, either directly or indirectly, to assist users who lack specialized expertise, while mimicking the decision-making process of human experts. By leveraging the expert knowledge they contain, these systems offer users precise solutions to their problems. The swift progress of industrial automation and intelligence has introduced increasingly complex decision-making challenges for many businesses. In manufacturing, managing quality control, assurance, and product design and development can be particularly challenging without effective decision-making capabilities [13]. Fault detection has received significant theoretical and practical attention in recent years in technological systems. Fault detection is a complex reasoning process, and it is one of the areas where artificial intelligence techniques have been successfully applied.

These techniques use association rules, reasoning, and decision-making processes that resemble the functioning of the human brain to solve fault detection problems [14]. The study examines data from years of use of expert systems (ESs) at various levels and functions, including a pilot experiment in which ESs were developed to perform two distinct roles in the same domain. The findings suggest that ESs serving in a supportive capacity are useful for Operational and tactical decision-making, but also facing challenges at the strategic level. As advisory systems, these ESs can improve decision-making, although their success depends on user engagement. In experiments, contrary to many users' expectations, an expert advisory system did not reduce users' time; however, an ES in a supportive role improved decision-making skills [15].

2. MATERIALS AND METHOD

Knowledge-Based Systems: A knowledge-based system is a computer system designed to analyse knowledge, data, and information from various sources to generate new insights. By leveraging artificial intelligence techniques, it can effectively solve problems, support human learning, and aid in decision-making. Examples of knowledge bases include a public library, a specialized information database, and whatis.com. In the context of information technology, a knowledge base refers to a machine-readable resource designed to share information that is typically available online or hosted online.
Decision Support Systems: A decision support system is a computerized tool designed to collect, analyse, and synthesize data to produce detailed information reports. Unlike standard operational applications, a DSS focuses solely on data collection and analysis to support decision-making processes.
Rule-Based Systems: Rule-based systems are a basic type of AI model that rely on a set of predefined rules to make decisions and solve problems. These rules, created by developers using human knowledge, guide the computer to process input data and produce outcomes. A rule-based international system (RBIS) is created through agreements on relations between states, international organizations, and structures, which are governed by common rules and standards of behaviour.
Intelligent Systems: Intelligent systems are advanced machines that sense and react to their environment. These systems can take many forms, including automated devices like Roomba, facial recognition software, and personalized shopping recommendations from Amazon. An intelligent information system is a combination of software, hardware, and skilled individuals who are experts in decision-making and integration processes across organizations. It includes artificial intelligence and reliability metrics, especially in the analysis of medical images.
Logic-Based Systems: Logic is often explored through the construction of what are called logical systems. A logical system is essentially a method for systematically listing all logical facts within a given area of logic, using recursive rules that can be applied repeatedly to their own conclusions. Logic-based learning is a specialized field within artificial intelligence, at the intersection of knowledge representation and machine learning. It involves the automated generation of logic-based programs using examples and existing domain knowledge.
Usability Evaluation: It refers to how effectively, a product or design can be used by a specific user to achieve a specific goal in a specific environment efficiently and satisfactorily. Designers typically evaluate the usability of a design throughout the development process, from wireframes to the final product, to ensure optimal usability.
Knowledge Base Evaluation: A knowledge-based assessment is an assessment that measures a person's understanding and application of knowledge within a specific subject area. These assessments emphasize how a person applies Rather than testing their ability to recall that knowledge, facts, or complete specific tasks.
Performance Metrics: Performance measurement is the process of assessing the effectiveness and efficiency of programs, projects, and initiatives. It involves a systematic approach to collecting, analysing, and evaluating a program or project is progressing toward achieving its intended results, goals, and objectives.

GRA Method: The presence Different wireless network access technologies within the same geographic area provide users with flexible connection options and different quality of service for different types of traffic. The choice of a particular Network data is affected by factors such as rate, cost, latency, and other quality of service. However, users can switch between different networks, mobile devices require additional functions that facilitate vertical handover between heterogeneous networks, which is usually reserved for horizontal handovers between networks using the same access technology [16]. Various machining processes such as Drilling, turning, and milling are commonly used in manufacturing industries. In this process, material is removed using a rotating cutting tool called a drill bit, which creates burrs. The drill bit Used specifically to create a hole in a solid material. Achieving a smooth surface is a key goal in any manufacturing process and a key criterion for evaluating the quality of the drilled hole. Excessive Hardness can negatively affect the process and reduce the reliability of the product. This need for consistent quality and reduced roughness drives ongoing research to optimize machining parameters to reduce manufacturing costs and improve surface finish quality [17]. Fused silica (quartz) is considered a leading material in many engineering applications because of its properties including transparency, attractive Appearance, corrosion resistance, temperature stability and high hardness and strength. Electrical Discharge Machining and Electrochemical Machining are modern manufacturing techniques [18]. With the development of the global economy, the manufacturing industry is increasingly focusing on quality and time efficiency. As a result, non-traditional machining methods Laser machine, electrical discharge machine, chemical machine and abrasive water jet machine, etc. are becoming essential. The use of assist gases helps to remove molten metal from the cut kerfs, while cooling and protecting the focusing lens. Laser beam machining (LBM) is an ideal choice for industrial applications due to its narrow kerf width, high accuracy and ability to create complex shapes, fast production rates, and the ability to cut difficult materials. Various parameters in the LBM process are selected and optimized to achieve the desired results [19]. Rapid identification of plant species is essential for efficient nursery production. For a variety of plant materials, new control systems must be implemented in nurseries to prevent hybridization and maintain diversity and purity throughout the plant production and batch distribution process. Despite recent research, there is still limited understanding of the most effective method for accurate leaf sampling. Many studies of species discrimination have not addressed factors related to the nature of the samples, which can introduce variability. For example, mature trees have diverse canopies with leaves at different tonal levels [20]. Among various advanced machining processes, EDM is well suited for machining such materials. However, its main drawbacks are poor surface finish and low material removal rate which limit its application in manufacturing biomedical products with high surface quality. Recent developments in EDM have addressed these limitations, improving surface finish and MRR, and improving overall process efficiency [21]. The heavy-duty industry is particularly looking for load cells that are lightweight, robust and environmentally resistant. To meet these demands, new and improved methods are being developed, and improvements can be achieved through numerical simulation techniques. This can lead to improvements in existing products. The use of finite element analysis has significantly increased the use of computer and numerical simulation, which is driving the introduction of more intensive and effective computer-based approaches [22]. Recent advances in materials science have led to the development of composite materials and high-tech ceramics with excellent mechanical and thermal properties, as well as sufficient electrical conductivity. However, these materials are difficult to machine using traditional processes. As a result, new manufacturing concepts have emerged using unconventional Energy sources such as sound, light, mechanical forces, chemicals, electricity, electrons, and ions. In addition, unconventional machining methods can meet requirements such as surface finish and high precision. Electrical discharge machining is one of the earliest unconventional processes, based on the thermo-electric potential between the work piece and the electrode. EDM can machine any conductive material, making it a popular choice in manufacturing because it relies on electrical power for the machining process [23]. Surface integrity has always been a key factor in machining operations. In today’s rapidly changing market and economic conditions, improving surface integrity has become a top priority for the industry. With the introduction of advanced tools and equipment, many technologies are being developed in the machining industry that can improve surface quality, improve roughness, improve dimensional accuracy, material removal rate (MRR), and more. Milling is a versatile machining method widely used in industries such as mining, construction, railway cars and various types of vehicles. Most of these components are made from machined AA6063 T6 and are manufactured through continuous milling operations. [24]. Neural networks do not require the establishment of a predefined functional model between input and output. They also offer advantages such Self-learning, high fault tolerance, parallel processing, and distributed information storage. These features make them well suited for solving complex and non-creative problems. As a result, neural networks have gained significant popularity in various fields, especially in research focused on predicting stock market prices and rates of return [25]. A typical friction material consists of a resin binder, fibre reinforcement, abrasives, fillers, and lubricants. Asbestos was commonly used for many years due to its cost-effectiveness and favourable properties as a brake friction material. However, due to its carcinogenicity, environmental protection agencies have banned the use of asbestos, which has prompted the friction industry to search for alternative materials. The use of such materials is not only cost-effective, but also helps reduce environmental pollution. A high-quality friction material must have key performance-defining properties, including a high and stable friction coefficient, low fade, rapid recovery, excellent wear resistance, and low sensitivity to changes in load and speed, ensuring reliable and safe performance [26]. Photochemical machining (PCM) is one of the fastest growing non-traditional machining processes used to create two-dimensional, complex parts. The process combines light and chemical energy to remove material. Since no physical force is applied to the work piece, it results in stress- and burr-free parts. The process involves the controlled etching of the work piece material using a strong oxidative chemical mechanism. PCM is typically used to create components with simple shapes and large dimensions. Historically, it was mainly used for the manufacture of jewellery and decorative items [27]. The MTC is a multi-dimensional, anisotropic, and non-homogeneous system that is encapsulated in the conjunctiva or neurosis (perimysium). Computational methods are widely used modelling the mechanical behaviour of the MTC in biomechanics. To the best of our knowledge, this method has been applied to the MTC for the first time. It considers Microstructure of MTC and its components and calculates their influence on the overall response. Unlike FEM, DEM effectively captures the complex behaviour of the material through a straightforward singular concept and implementation [28]. Coffee Coffee beans are one of the most consumed beverages worldwide, and one of the most traded commodities, with production reaching 8.8 million tons in 2012. Known for its flavour, aroma, and stimulant effects, coffee also stands out. It has a high antioxidant capacity (AC) Compared to other popular beverages such as black and green tea, cocoa, fruit juices, and red and white wine. Antioxidant capacity (AC) of coffee is largely attributed to phenolic compounds, with chromogenic acids being the most important. However, other compounds in coffee, such as Mallard reaction products (mostly in the form of melanoidins), tocopherols, and caffeine, play a significant role and should not be overlooked. [29].

3. ANALYSIS AND DISCUSSION

TABLE 1. Expert Systems

	Functional Evaluation	Usability Evaluation	Knowledge Base Evaluation	Performance Metrics
Knowledge-Based Systems	11.00	87.00	91.00	77.00
Decision Support Systems	36.00	66.00	22.00	50.00
Rule-Based Systems	48.00	23.00	33.00	90.00
Intelligent Systems	91.00	78.00	45.00	23.00
Logic-Based Systems	52.00	66.00	65.00	41.00

Table 1 presents the evaluation of various expert systems using the GRA (Grey Correlation Analysis) method on four criteria: functional evaluation, utility evaluation, knowledge base evaluation, and performance metrics. Knowledge-based systems show high overall scores, especially excelling in the knowledge base evaluation (91.00). Decision support systems have a variety of ratings, with significantly lower scores in the knowledge base evaluation (22.00). Rule-based systems perform strongly in the performance metrics (90.00), but score low in the utility evaluation (23.00). Intelligence systems, while ranking high in the functional evaluation (91.00), rank low in the performance metrics (23.00). Logic-based systems have stable but moderate scores in all categories.

FIGURE 1. Expert Systems

Figure 1 shows the evaluation of expert systems using the GRA method on four criteria. Knowledge-based systems excel in the knowledge base rating (91.00), while decision support systems show variation, especially in the knowledge base rating (22.00). Rule-based systems perform better on performance metrics (90.00), and intelligence systems score higher on the operational rating (91.00).

TABLE 2. Normalized Data

	Functional Evaluation	Usability Evaluation	Knowledge Base Evaluation	Performance Metrics
Knowledge-Based Systems	0.0000	1.0000	0.0000	0.1940
Decision Support Systems	0.3125	0.6719	1.0000	0.5970
Rule-Based Systems	0.4625	0.0000	0.8406	0.0000
Intelligent Systems	1.0000	0.8594	0.6667	1.0000
Logic-Based Systems	0.5125	0.6719	0.3768	0.7313

Table 2 presents the normal data for expert systems evaluated using the GRA method on four criteria: functional evaluation, usability evaluation, knowledge base evaluation, and performance metrics. Intelligent systems receive higher normal scores on functional evaluation (1.0000) and performance metrics (1.0000), indicating better performance. Knowledge-based systems lead in usability evaluation (1.0000) but score lower in knowledge base evaluation (0.0000). Decision support systems excel in knowledge base evaluation (1.0000) and maintain strong scores on performance metrics (0.5970). Rule-based systems exhibit variability, achieving high scores on knowledge base evaluation (0.8406) but scoring zero on usability evaluation and performance metrics.

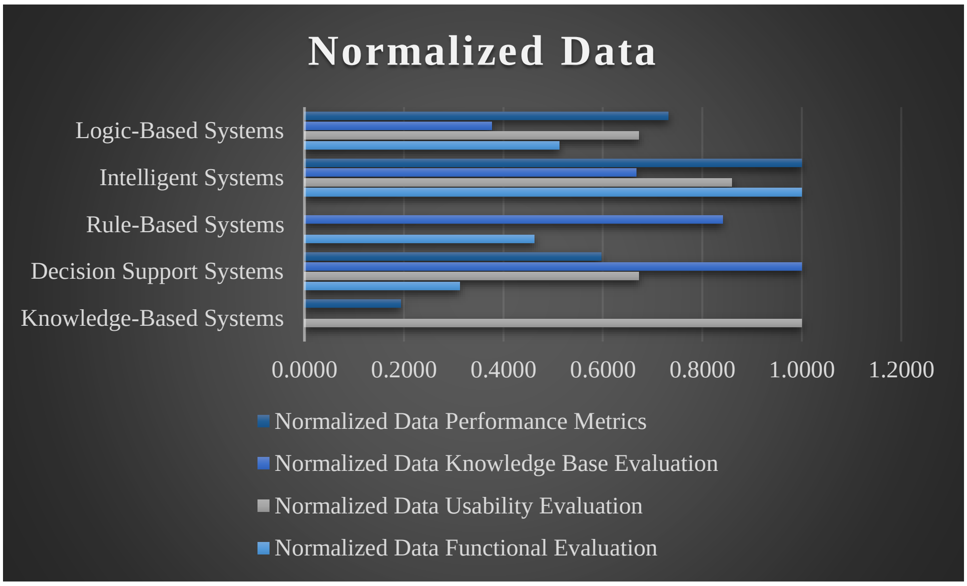

FIGURE 2. Normalized data

Figure 2 illustrates the normalized data for expert systems based on the GRA method. Intelligent systems score high on the operational evaluation and performance metrics (1.0000). Knowledge-based systems score well on the usability evaluation (1.0000) but score very low on the knowledge base evaluation. Decision support systems lead on the knowledge base evaluation (1.0000).

TABLE 3. Deviation sequence

	Functional Evaluation	Usability Evaluation	Knowledge Base Evaluation	Performance Metrics
Knowledge- Based Systems	1.0000	0.0000	1.0000	0.8060
Decision Support Systems	0.6875	0.3281	0.0000	0.4030
Rule-Based Systems	0.5375	1.0000	0.1594	1.0000
Intelligent Systems	0.0000	0.1406	0.3333	0.0000
Logic-Based Systems	0.4875	0.3281	0.6232	0.2687

Table 3 presents the order of deviation of expert systems evaluated using the GRA method on four criteria: functional evaluation, usability evaluation, knowledge base evaluation, and performance metrics. Knowledge-based systems show the highest deviation on functional evaluation and knowledge base evaluation (1.0000), but score the lowest on usability evaluation (0.0000). Decision support systems have the lowest deviation on knowledge base evaluation (0.0000) and moderate scores on other metrics. Rule-based systems show significant deviation on usability evaluation and performance metrics (1.0000). Intelligence systems show the lowest deviation on functional evaluation and performance metrics (0.0000), while logic-based systems show balanced and moderate deviation on all metrics.

TABLE 4. Grey Relation Coefficient

	Functional Evaluation	Usability Evaluation	Knowledge Base Evaluation	Performance Metrics
Knowledge-Based Systems	0.3333	1.0000	0.3333	0.3829
Decision Support Systems	0.4211	0.6038	1.0000	0.5537
Rule-Based Systems	0.4819	0.3333	0.7582	0.3333
Intelligent Systems	1.0000	0.7805	0.6000	1.0000
Logic-Based Systems	0.5063	0.6038	0.4452	0.6505

Table 4 summarizes the Grey correlation coefficient (GRA method) for various expert systems on four criteria: functional evaluation, utility evaluation, knowledge base evaluation, and performance metrics. Intelligent systems exhibit the highest coefficients on functional evaluation and performance metrics (1.0000), indicating strong performance. Knowledge-based systems excel in utility evaluation (1.0000) but score low on other criteria. Decision support systems lead in knowledge base evaluation (1.0000) and show moderate coefficients in other areas. Rule-based systems perform well on knowledge base evaluation (0.7582) but have a low coefficient on utility evaluation (0.3333). Logic-based systems maintain balanced but moderate coefficients overall.

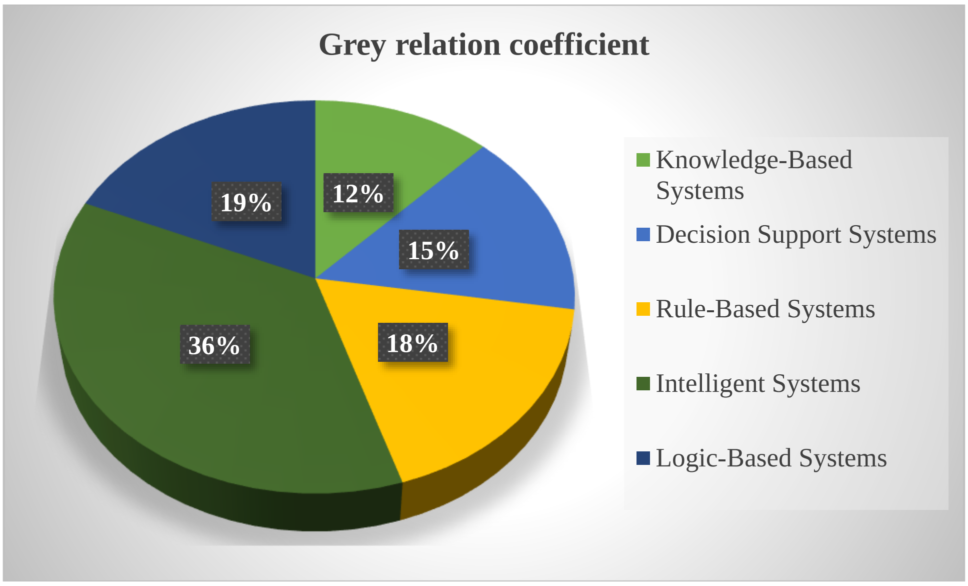

FIGURE 3. Grey relation coefficient

Figure 3 shows the Grey correlation coefficient for expert systems based on the GRA method. Intelligent systems excel in the performance and efficiency metrics (1.0000). Knowledge-based systems lead in the usability metric (1.0000), while decision support systems achieve the highest coefficient in the knowledge base metric (1.0000). Rule-based systems and logic-based systems show moderate coefficients overall.

TABLE 5. Result of final GRG Rank

	GRG	Rank
Knowledge-Based Systems	0.5124	4
Decision Support Systems	0.6446	2
Rule-Based Systems	0.4767	5
Intelligent Systems	0.8451	1
Logic-Based Systems	0.5514	3

Table 5 presents the final Grey Relational Grade (GRG) estimated using the GRA method and the corresponding ranking of expert systems. Intelligence systems maintain the highest GRG (0.8451), earning the first rank due to their excellent overall performance. Decision support systems are in second place with a GRG of 0.6446, showing strong results across several metrics. Logic-based systems are in third place with a GRG of 0.5514, reflecting balanced but moderate performance. Knowledge-based systems are in fourth place with a GRG of 0.5124, showing improvement in some areas but declining overall. Rule-based systems are last (GRG: 0.4767), highlighting the need for improvements across several metrics.

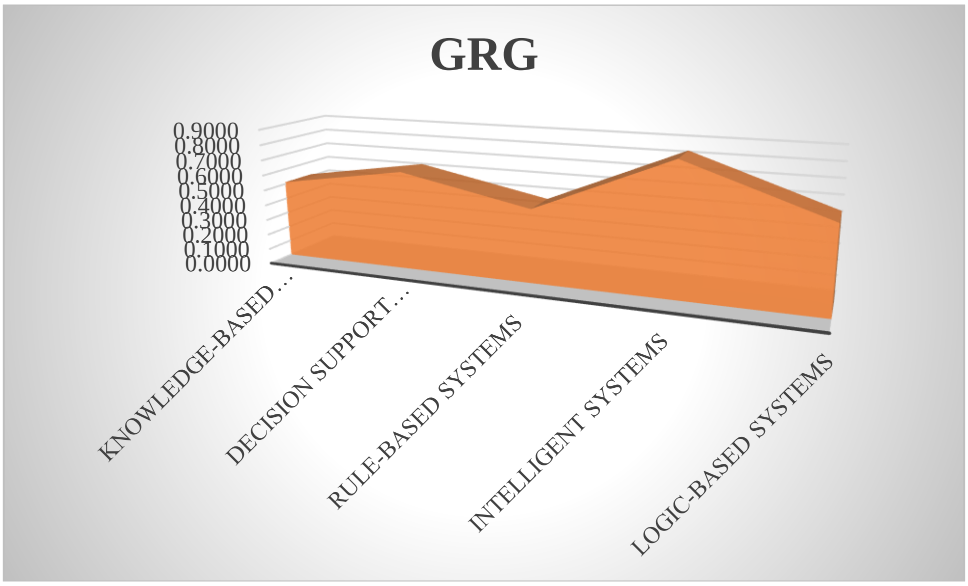

FIGURE 4. GRG

Figure 4 illustrates the Grey Relational Grade (GRG) for expert systems estimated using the GRA method. Intelligence systems achieve the highest GRG (0.8451), followed by decision support systems (0.6446). Logic-based systems are third (0.5514), knowledge-based systems (0.5124) and rule-based systems (0.4767) are at the lowest positions.

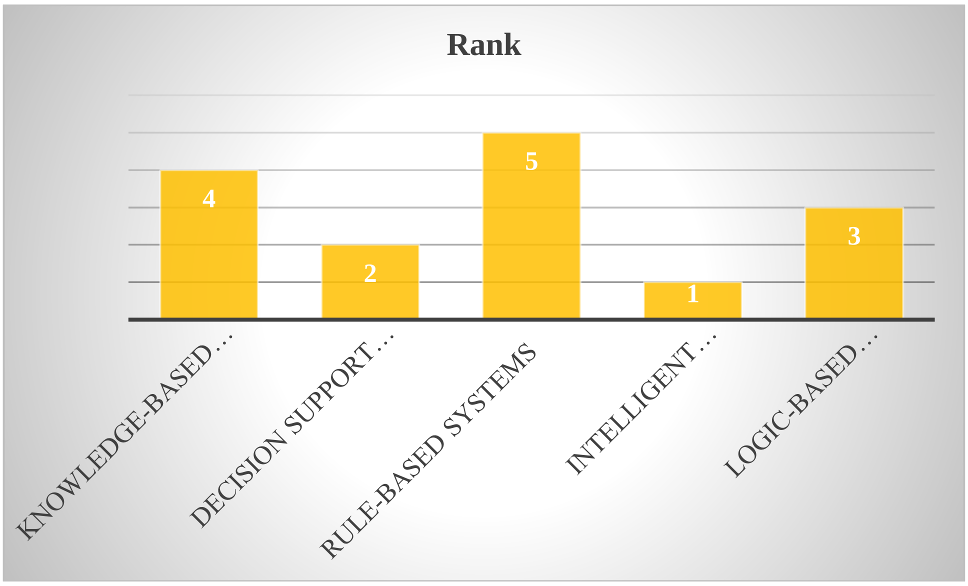

FIGURE 5. Shown the Rank

Figure 5 presents the rankings of expert systems based on the GRA method. Intelligent systems occupy the first place, exhibiting the best performance. Decision support systems occupy the second place, followed by logic-based systems in the third place. Knowledge-based systems occupy the fourth place, while rule-based systems occupy the fifth and final place, indicating room for improvement.

4. CONCLUSION

The evaluation of various expert systems using the Grey Relational Analysis (GRA) method has revealed significant insights into their comparative performance across a number of criteria. The analysis, which examined functional evaluation, utility evaluation, knowledge base evaluation, and performance metrics, demonstrates clear differences in the capabilities and performance of the various expert system types. Intelligent Systems emerged as the best overall, achieving a high Grey Relational Grade (GRG) of 0.8451, taking first place. This superior performance can be attributed to their exceptional scores on the functional evaluation and performance metrics, where they scored 1.0000. Their success highlights the importance of adaptive and sophisticated systems in modern applications. Decision Support Systems proved to be strong contenders, coming in second place with a GRG of 0.6446. Their particular strength in knowledge base evaluation and balanced performance across other metrics demonstrates their reliability in supporting decision-making processes. This positioning confirms their continued relevance in the organizational decision-making framework. Logic-based systems earned a respectable third place (GRG: 0.5514), while knowledge-based systems and rule-based systems ranked fourth and fifth, respectively, with GRGs of 0.5124 and 0.4767. While these rankings have specific strengths – such as their excellence in the assessment of the utility of knowledge-based systems – they may need improvement in other areas to improve their overall performance. The analysis reveals that success in modern expert systems requires a balanced approach across all assessment criteria, rather than excelling in one or two areas. This finding has important implications for the future development and implementation of expert systems, suggesting that developers should focus on creating well-rounded systems that consistently perform across multiple dimensions. The results also indicate that traditional rule-based approaches, while valuable, need to evolve to meet contemporary demands. Incorporating the superior performance, adaptability, and learning capabilities of intelligent systems into expert systems will be critical to future advancements in the field, it says. This comprehensive assessment provides organizations with valuable guidance in selecting expert systems that are appropriate for their specific needs, while also highlighting areas where different types of systems can be improved. As artificial intelligence and expert systems continue to evolve, these insights will help guide future development efforts and system implementations, ensuring that they best serve their intended purposes by maintaining high standards across all evaluation criteria.

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