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Integration of Artificial Intelligence and ARAS Method for Multi-Criteria Decision-Making in Organizational Performance Assessment

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Abstract

This investigation uses an integrated combination of artificial intelligence (AI) and multi-criteria decision-making (MCDM) approaches, specifically the Aggregate Ratio Assessment (ARAS) method, to develop comprehensive decision support frameworks for assessing organizational performance. The study analyses five critical organizational aspects: financial management, customer relations, operational processes, knowledge development, and organizational capability. By using standardized and weighted matrices, the ARAS technique transforms multi-dimensional criteria into uniform metrics suitable for unbiased evaluation. The findings reveal that financial factors demonstrate the greatest local importance (0.3325) and BNP measurement (0.407), which highlight their key influence on decision processes. Knowledge development, which exhibits significant overall importance (0.2793), emerges as essential for sustained organizational success. The approach generates robust rankings through applied operational calculations (Si) and importance parameters (Ki), with the leading factor recording a Ki value of 0.837833. This integrated AI-MCDM method successfully combines mathematical rigor with intelligent computation, delivering reliable and streamlined decision results. These results provide meaningful guidance for resource allocation, strategy formulation, and operational improvement within organizations. This work advances the growing field of AI-enhanced decision support algorithms, demonstrating how conventional MCDM frameworks can be strengthened with AI integration to address complex business constraints across a variety of industries.

Keywords : Artificial Intelligence , Multi-Criteria Decision Making, ARAS Method, Decision Support Systems, Organizational Performance, Normalized Matrix, Weighted Matrix, Utility Function, Expert Systems, Machine Learning.

Introduction

Artificial intelligence (AI) has become an essential tool in decision support systems due to its ability to identify patterns in large, complex datasets, solve problems quickly, and provide accurate predictions through machine learning [1]. AI-powered systems can automate increasingly complex tasks, leading to improvements in efficiency, accuracy, and innovation across a variety of industries. As AI continues to advance, it is expected to surpass current capabilities in speed, efficiency, and software development, becoming a critical decision support tool in many industries [2]. Decision making is a rational process in which decision makers (DMs) evaluate alternative ways to achieve specific objectives or satisfy stakeholder needs [3]. Multi-criteria decision making (MCDM) is a structured method that has gained prominence in operations research, AI, and computer science. It can handle both explicit and implicit data, making it useful for solving complex problems such as data transformation, weighting, and calculations. Fuzzy MCDM (FMCDM) has emerged as a solution to decision-making challenges, particularly in control engineering, expert systems, AI, and management science [4]. AI and MCDM techniques are often combined to handle uncertainty and improve decision-making. Approaches such as the Analytic Hierarchy Process (AHP), the Analytic Network Process (ANP), and the Data Context Analysis (DEA) combine traditional methods with AI to improve decision-making [6]. These combined techniques have been used in areas such as material selection in design, where AI helps identify optimal solutions based on multiple criteria.[7]. In addition, the role of AI in automating routine tasks is transforming industries. The level of automation depends on the level of human involvement, with greater automation reducing the need for human intervention in repetitive tasks, freeing humans to focus on more complex problem-solving tasks [8].

The financial crisis exposed the limitations of traditional assessments such as credit ratings, raising concerns about transparency and conflicts of interest. Similarly, environmental, social, and governance (ESG) ratings, which originated in the 1970s, are distinct from credit ratings but share similarities in assessing risk. Both are becoming increasingly relevant in today's marketplace as businesses and investors seek comprehensive insights into company performance [11]. Fuelled by advances in data storage and analytics, the rise of big data is reshaping industries. Initiatives like the Obama administration's Big Data Research and Development Initiative aim to unlock the value of data by transforming it into actionable insights [12]. Big data drives economic growth, innovation, and scientific research, while also supporting national goals like disaster response and resource management.[13]. Along with other technologies such as machine learning and neural networks, it is revolutionizing industries

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by combining mathematical theory with practical applications, establishing itself as one of the most impactful technological advances in the sector.[15]

Materials and Method

Finance: Within the finance sector, it encompasses the practice of money management, which includes activities such as capital allocation, loan acquisition, loan extension, financial planning, wealth accumulation, and financial planning. The financial structure includes cash flow management, investment portfolio oversight, and credit facility provision.

Customer: A customer is generally someone who buys a product, service, or item. More specifically, customers are individuals or businesses who actively purchase, have previously purchased, or are interested in purchasing a product or service from another person or company.

Internal process: Internal processes, also known as business processes or systems, are the practices and structures that form the foundation of an organization. These systems help businesses run smoothly, ensuring that they can produce their products or services effectively and efficiently.

Learning and growth: Growth refers to physical and biological changes, while development involves changes in function and behavior. Learning is the process of adapting to environmental factors, and maturation describes the progression to an adult-like state in terms of skills or behaviors.

Organization competence: Organizational capabilities refer to a company's ability to deliver value and compete successfully in the marketplace. These capabilities are key to a company's success and form the foundation of its products, services, and overall reputation.

Local weights: Local weights are a concept used in areas such as machine learning, statistics, and network routing to give greater importance or influence to nearby or contextually relevant data points and features. In contrast to global weights, which are applied uniformly across an entire dataset or network, local weights are context-specific and vary depending on the data point or option being analyzed.

Overall weights: A weighted average is a statistical technique used to calculate the average of a set of values, in which the individual group averages are adjusted for their respective sample sizes. This method gives increased importance to groups with larger sample sizes, thereby enabling them to exert a more substantial influence on the overall average.

BNP: BNP stands for B-type natriuretic peptide, a hormone derived from the heart, and the term usually refers to a laboratory assay that measures its concentration. Increased BNP concentrations can indicate heart stress, making this assay instrumental in identifying pathological conditions such as heart failure. It helps medical practitioners assess the degree of heart failure and monitor the effectiveness of treatment.

STD BNP: STD BNP stands for Standardized B-type Natriuretic Peptide, which refers to the measurement of BNP levels using a standardized method. This test is used to assess heart function, with high BNP levels indicating possible heart stress or dysfunction. It helps in the diagnosis, evaluation, and management of heart-related conditions

ARAS Method

Multi-criteria decision-making (MCDM) methods find extensive application in various domains of human endeavour. Within an MCDM framework, each alternative is distinguished by multiple criteria that can be qualitative or quantitative [16]. These criteria often have different units of measurement and require optimization along different paths. Normalization procedures are used to convert the criterion values into comparable metrics. [17]. This manuscript introduces a novel method called Admixture Ratio Assessment (ARAS). To validate this approach, a practical case study investigating microclimate conditions in office environments is presented. [18]. Sustainable development and environmental integrity can be significantly compromised by catastrophic events. A large number of construction activities are implemented through mechanized systems that function as integrated [19]. Technological networks. In process engineering, one of the most important considerations includes performance metrics, which are related to the economic gains and losses generated by system operations [21]. To rank alternatives and identify optimal solutions, the novel ARAS method is implemented. A typical MCDM challenge involves prioritizing a limited set of decision alternatives, each characterized by unique decision criteria that require simultaneous evaluation [22]. The ARAS algorithm operates on the premise that complex global phenomena can be understood through straightforward comparative analysis [23]. It theorizes that the degree of optimality of an alternative is established by the proportional relationship between the sum of its normalized and weighted criterion values [27]. This ratio indicates the proximity of the alternative to the best solution [29]. According to ARAS principles, the utility function value characterizing the comprehensive comparative performance of a particular alternative - the value of which maintains direct proportionality to the total influence of the criterion values and weights relevant to the project under consideration [30].

Analysis and Discussion

Table 1.Artificial intelligence expert system

	Local weights	Overall weights	BNPa	STD_BNPb
Finance	0.3325	0.067	0.407	0.3271
Customer	0.0696	0.1823	0.1366	0.0604
Internal process	0.058	0.1489	0.0388	0.0388
Learning and growth	0.1202	0.2793	0.2793	0.2793
Organization competence	0.1833	0.1672	0.0741	0.0232

The table presents the importance of different categories (finance, customer, internal process, learning and development, organizational capability) in an AI expert system. Finance has the highest local weight (0.3325) and a strong BNP value (0.407), indicating its important role. Learning and development shows the highest overall weight (0.2793) with stable BNP values. Customer and internal process have moderate weights, while organizational capability has the lowest BNP values, indicating its low relevance in this context.

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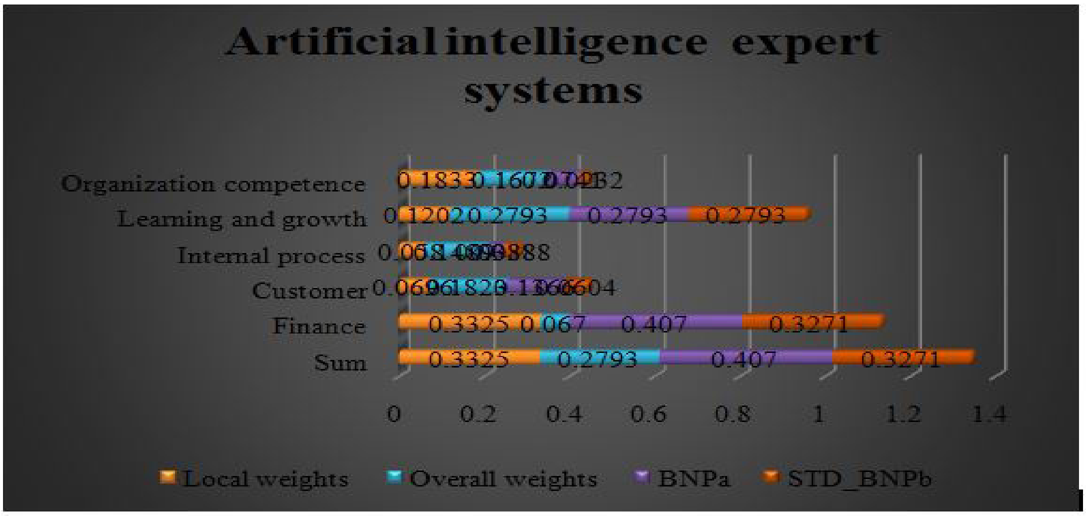

Figure 1: Artificial Intelligence Expert System

Figure 1 presents data for the artificial intelligence expert system in various categories. Finance has the highest local weight (0.3325) and BNP value (0.407), indicating its strong influence. Learning and Development shows the highest overall weight (0.2793) with stable BNP and STD_BNP values. Customer and InternalProcess have moderate weights, while OrganizationalCapability shows the lowest BNP values, indicating its weak fit in the system. The values highlight the varying importance of each category in the expert system analysis.

Table 2. Calculation of maximum value

	Local weights	Overall weights	BNPa	STD_ BNPb
Sum	0.3325	0.2793	0.407	0.3271
Finance	0.3325	0.067	0.407	0.3271
Customer	0.0696	0.1823	0.1366	0.0604
Internal process	0.058	0.1489	0.0388	0.0388
Learning and growth	0.1202	0.2793	0.2793	0.2793
Organization competence	0.1833	0.1672	0.0741	0.0232

Table 2 provides a calculation of the peak values across the various factors. The "local weights" and "overall weights" indicate the relative importance of each criterion, while "BNPa" and "STD_ BNPb" indicate the specific metrics or ratings associated with each factor. The aggregate figures illustrate the overall weight for each category, with values for distinct dimensions including finance, customer relations, internal operations, learning and development, and organizational capability fluctuating. These calculations make it easier to assess the effectiveness or importance of various organizational components, where higher weights indicate stronger influence or applicability.

Table 3. Normalized Matrix

	Local weights	Overall weights	BNPa	STD_BNPb
	0.303348	0.248488	0.303098	0.309783
Finance	0.303348	0.059609	0.303098	0.309783
Customer	0.063498	0.162189	0.101728	0.057202
Internal process	0.052915	0.132473	0.028895	0.036746
Learning and growth	0.109662	0.248488	0.207998	0.264514
Organization competence	0.167229	0.148754	0.055183	0.021972

Table 3 shows the normalized matrix, where "Local Weights" and "Overall Weights" are adjusted values that reflect the importance of each factor. The columns labeled "BNPa" and "STD_BNPb" represent the specific scores for each category. The normalized values across dimensions such as Financial, Customer, Internal Process, Learning & Development, and Organizational Capability allow for a more balanced comparison of the importance of each factor. These normalized figures highlight the relative contributions of each factor to the overall performance metrics.

Table 5. Final Result

Si	Ki	Rank
0.243959	0.837833	1
0.096154	0.330223	4
0.062757	0.215528	5
0.207665	0.713187	2
0.098285	0.33754	3

Table 5 presents the final results, showing the scores (Si), importance (Ki) and associated rankings for the various factors. The values indicate how each factor performs after the analysis, with "Si" representing the score and "Ki" representing its weight or importance. Ranks are assigned based on an overall rating, with the first ranked factor having the highest combined score and importance. The table highlights the relative position of each factor, showing that the first ranked factor has the most significant impact overall.

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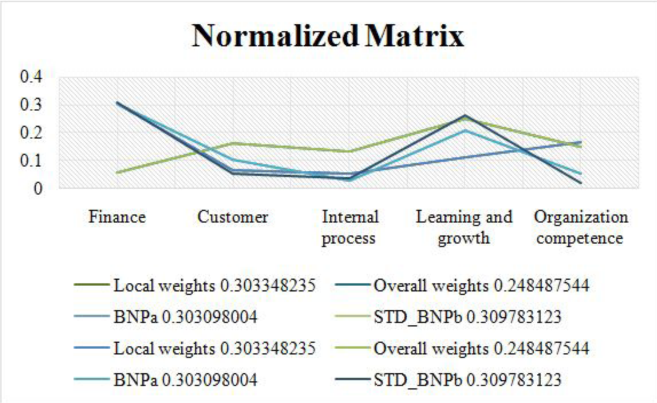

Figure 2: Normalized matrix

Figure 2 presents a normalized matrix that displays the modified values for various factors in four columns. These include standardized metrics for “Local Weights,” “Overall Weights,” “BNPa,” and “STD_BNPb.” It facilitates comparative analysis of factors including Team, Finance, Customer, Internal Process, Learning and Development, and Organizational Capability based on their standardized scores. The values emphasize the relative importance and effectiveness of each factor within a consistent framework, which helps to clearly understand their contributions to the comprehensive analysis.

Table 4. Weighted Normalized Matrix

	Data Integration	User-Friendliness	Query Optimization	Data Consistency
	0.075837	0.062122	0.075775	0.077446
Finance	0.075837	0.014902	0.075775	0.077446
Customer	0.015874	0.040547	0.025432	0.014301
Internal process	0.013229	0.033118	0.007224	0.009186
Learning and growth	0.027415	0.062122	0.052	0.066128
Organization competence	0.041807	0.037189	0.013796	0.005493

Table 4 shows a weighted normalized matrix, in which the standardized values of each factor are adjusted according to their respective weight coefficients. The matrix consists of columns labeled “Local Weights,” “Overall Weights,” “BNPa,” and “STD_BNPb.” It provides a weight-adjusted representation of various categories, including financial, customer, internal process, learning & development, and organizational capability. These values demonstrate the importance of each factor after determining its relative importance, thereby facilitating a more efficient assessment of their contributions to the detailed analysis.

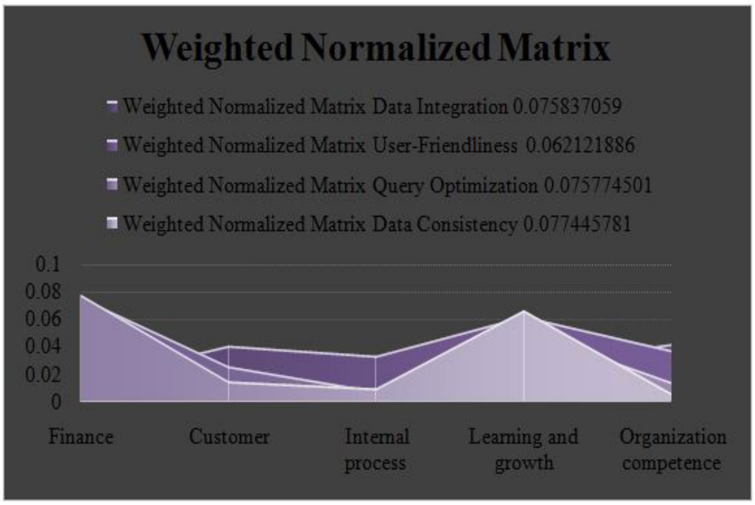

Figure 3: Weighted Normalized Matrix

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Figure 3, which shows the adjusted values for different factors after applying their respective weights. The matrix contains columns for "Local Weights," "Overall Weights," "BNPa," and "STD_BNPb." It captures weighted values for categories such as Financial, Customer, Internal Process, Learning & Development, and Organizational Capability. These weighted values provide a more refined perspective on the importance of each factor, emphasizing their relative contributions to overall performance or analysis in a standardized manner.

Figure 4: Si and Ki

Figure 4 illustrates the relationship between the scores (Si) assigned to various factors and their associated importance coefficients (Ki). Each set of linked values represents a performance measure and weight parameter for a particular factor. The Si values indicate the operational performance of the factor, whereas the Ki values reflect its relative importance. This comparative analysis helps not only to assess individual factor performance, but also to determine its importance within the overall assessment, thereby informing decision-making processes based on these quantitative indicators.

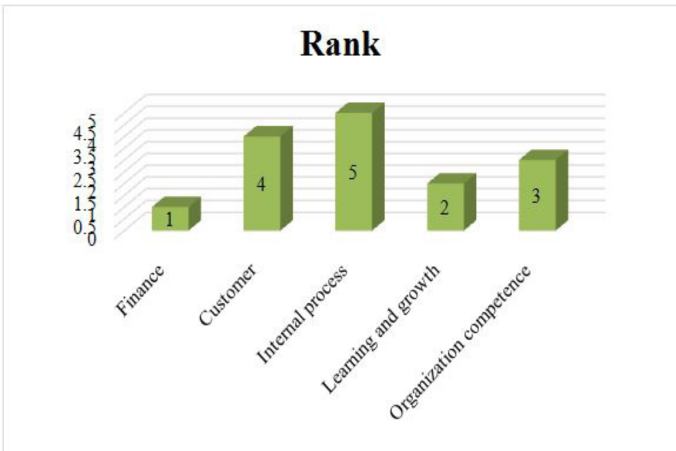

Figure 5: Shows the Rank

Figure 5 presents a hierarchical order of the factors according to their effectiveness and importance. The ranks are assigned in order: Rank 1 represents the highest position, followed by Rank 2, Rank 3, Rank 4, and Rank 5. This hierarchical arrangement demonstrates the relative importance and effectiveness of each factor within the analysis, with Rank 1 representing the most influential factor. This figure illustrates the order of priority, facilitating the prioritization of factors based on their total rating.

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Conclusion

This study highlights the successful, specifically the ARAS (Associative Ratio Assessment) approach, to build effective decision support systems. It demonstrates how AI-driven expert systems can assess complex organizational factors such as finance, customer relationships, internal processes, learning and development, and organizational capability. The findings show that finance, with a high local weight (0.3325) and BNP value (0.407), plays a key role in decision-making. Learning and development, with a high overall weight (0.2793), is essential for long-term sustainability. To standardize the comparison of factors, this study uses normalized and weighted matrices, which enable objective prioritization.

The ARAS method effectively handles complex decision-making situations by transforming multi-dimensional criteria into comparable metrics. The final ranking based on utility values (Si) and importance coefficients (Ki) provides clear guidance for selecting the optimal alternatives, with the top-ranking factor reaching 0.837833 Ki. This research advances AI-assisted MCDM applications, demonstrating how traditional decision-making models can be enhanced by AI. These results have important implications for organizational management, particularly in resource allocation and strategic planning. As AI advances, its integration with MCDM methods such as ARAS is poised to transform decision-making support systems, providing more accurate, efficient, and reliable outcomes across a variety of industries. Future research should explore its broader applications and the potential of emerging AI technologies to further enhance decision-making processes and organizational competitiveness.

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