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Comparative Evaluation of Ai Techniques Using the MOORA Method in Supply Chain Operations

Suresh Pandipati*

Enterprise Data Architect and IT Senior Project Manager, Richardson, TX, USA

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ABSTRACT

The recent pandemic has limited vehicle movement and disrupted the overall efficiency of supply chain networks. Consequently, the idea of supply chain resilience has drawn a lot of interest from scholars and industry professionals. Businesses must focus on safeguarding and enhancing their market position to avoid disruptions.

This study emphasizes how crucial supply chain resilience is becoming, particularly in response to the pandemic, globalization, and technological advancements. It examines how Supply chain efficiency could be enhanced by artificial intelligence (AI) performance, financial management, and risk mitigation. The research offers insightful information about the effects of AI and provides actionable recommendations for improving supply chain operations.

Procurement, Production, Inventory Management, Distribution, Transportation. Evaluation Preference: ANN, Rough set theory, Machine Learning, Expert System.

The results Distribution achieved the highest rank, while Production received the lowest rank being attained.

*Corresponding author. e-mail: suresh.pandipati@gmail.com

1. **Introduction**

The most recent pandemic has limited vehicle movement and disrupted the overall performance of Supply chain networks have been significantly impacted, bringing the concept of supply chain resilience to professionals' and academics' notice. To safeguard and strengthen their market positions and prevent disruptions during crises such as COVID-19, companies must make real efforts to integrate resilience into their supply chain systems. Beyond the pandemic, rapid globalization, growing customer demands, and the emergence of new competitors have The unstable and turbulent corporate climate have heightened, amplifying the demand on businesses to optimize and effectively manage their supply chains. [2]Due to the uncertainties surrounding global supply chain financing (SC), Supply chain finance (SCF) has garnered growing research interest. However, there remains anabsence of thorough research on how financial services are integrated into supply chains managementare scarce and fragmented. This article examines the recovery efforts following the 2008 financial crisis and the uncertainties affecting SCF providers and brokers Following the COVID-19 pandemic.

At the same time, advanced technologies like the business environments where SCF operates are changing due to artificial intelligence (AI) operates. To navigate these evolving dynamics, the article employs a fuzzy set theory method for improve relative validity of institutions within the standard SCF framework and highlight innovative integration of AI concepts. This approach aims to identify inefficiencies and challenges within SCF systems. The findings demonstrate that AI offers substantial economic potential and permits supply networks to be used more effectively. Furthermore, the piece adds to the theoretical understanding of SC financing and expands managerial insights for improving performance. [3] The adoption SCRM using artificial intelligence (AI) is receiving increasing attention. However, research on its enterprise-wide adoption across various industry sectors in India is limited. The aim of this research is to examine the variables that impact adoption, implementation intentions, and reuse intentions of AI in SCRM within Indian organizations. The research focuses on industries such as retail, wholesale, logistics, consumer durables, and consumer packaged goods (CPG). [4]The effectiveness of artificial intelligence (AI) technology in assisting businesses and the economy is a topic of debate among academics. While AI is not a comprehensive solution, some argue that it has the potential to transform businesses and the global economic environment by offering advantages like more output and fewer mistakes made by people, improved decision-making, accurate prediction of customer preferences, and increased sales. However, AI adoption is currently concentrated in a few areas, creating an "AI gap" that could exacerbate inequalities in global social, economic, and cultural sectors. In addition, because AI relies largely on software, it is vulnerable to potential flaws that require attention.

In short, opinions on AI technology vary, highlighting the importance of empirical analysis to determine its ability to address specific challenges such as improving supply chain resilience and efficiency. [5]This review aims to categorize the different subfields of artificial intelligence (AI) and investigate how it is used in the supply chain industry. The

study emphasizes four critical supply chain operations, including Purchasing and procurement, manufacturing and inventory control, distribution, and demand forecasting and planning and transportation. Machine learning (ML), which focuses on predicting behavior, is widely used to address a number of supply chain challenges, particularly in forecasting and demand planning. ML uses information from sources like social media to overcome predicting future demand, minimizing the bullwhip, and predicting issues during disasters effect by sharing accurate demand information with supply chain partners, generate accurate six-month forecasts, and generate reliable sales projections. [6] The purpose SCP focuses on managing Planning for medium- to long-term projects throughout the whole supply chain. It encompasses the coordination of production and logistics resources to meet customer orders, relying on resource planning informed by forecasted customer demand. Essential activities within SCP include Purchasing, production, and supply planning are all based on demand and network planning, as well as capacity testing to determine the promise/commitment of availability.

In the short term, activities such as purchasing planning, scheduling, ordering, and short-term supply planning contribute to supporting SCP. [7] Given its transformative potential, artificial intelligence (AI) is becoming increasingly important Supply chains face numerous challenges, making innovative organizational and technological strategies crucial. The growing The use of AI in supply chain collaboration has highlighted the need for a thorough examination of recent and historical changes in this varied and dispersed domain. By systematically analyzing 83 articles, this review offers valuable insights into key research trends and their progression over time investigation and use of AI in supply chain cooperation over the past decade. Helping researchers and practitioners better navigate this topic; the review provides clarity and depth, while also identifying future research directions. The findings are summarized in a conceptual framework for AI-driven cooperation throughout the supply chain, and a study plan is proposed. [8]Artificial intelligence (AI) is frequently used to examine large amounts of data techniques that can manage large amounts of data to support clinical research. However, while there is extensive research on how AI and big data analytics (BDA) interact at the clinical level, there is limited integration of this research in the framework of enhancing hospital supply chain operations, especially with regard to green standards. Our research explores the function of BDA in conjunction with AI (BDA-AI) in to our knowledge; there hasn't been much focus on enhancing environmental performance (EP) in hospitals. [9] Artificial Intelligence (AI) technology can analyze and assess alternatives using multifaceted data in dynamic situations, like as interruptions in the supply chain.

The importance of resilient information systems is examined in this study in such contexts in mitigating risks during disruptive situations in supply chain operations. A qualitative approach was used using semi-structured conversations with supply chain specialists. Thematic analysis was employed in order to determine emerging categories. The Results indicate important gaps in existing information systems and demonstrate How AI-powered solutions may enhance supply chain ecosystem that have been disrupted, resulting in lower costs and more productivity at various scales. [10] This study makes a unique theoretical contribution by exploring artificial intelligence as a factor in strategic human resource management and its link to supply chain agility, offering a fresh perspective in the information systems literature. Additionally, organizational flexibility has rarely been studied as a moderating factor between supply chain agility and resilience. The findings confirm that greater organizational flexibility strengthens supply chain resilience, thus contributing to the logistics literature.

In addition to the significant influence of external factors on supply chain agility and resilience, the results also reveal strong correlation coefficients (R^2). For instance, the combination of business culture, competitive intensity, human capital development, artificial intelligence, leadership, and employee capabilities accounted for 80% of the variance in supply chain agility, supporting the validity of the proposed research model.[11]Our study provides new theoretical insights into how organizations in emerging economies can prevent supply chain disruptions (SCDs). These insights are based on interviews with senior managers from three countries with expertise in supply chains – Indonesia, Malaysia, and Pakistan. As far as we are aware, this is the first study to examine how artificial intelligence (AI) can be incorporated into entire business processes.

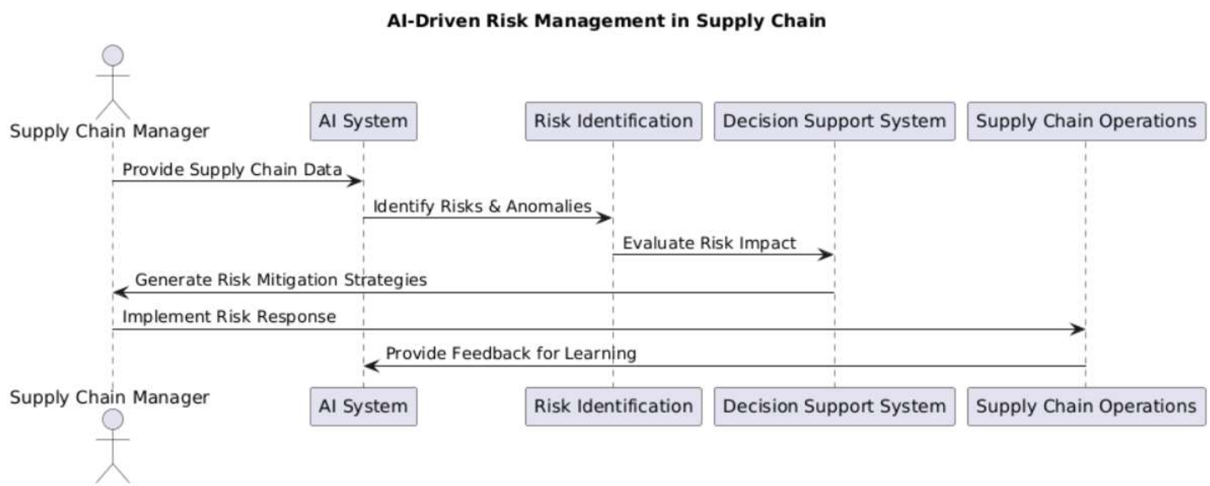
to mitigate This study investigates how supply chain disruptions (SCDs) are impacted by fake news and misinformation (FNaD). Our paradigm demonstrates the usefulness of AI and supply chain literature in tackling SCDs caused by fake news and misinformation campaigns. Using a qualitative methodology, we integrated AI research with studies on fake news to explore ways to improve decision-making efficiency in Supply chain operations have been impacted by previous research that has enhanced the understanding of fake news detection mechanisms through the use of graphs and abstraction techniques, and our study builds on this foundation by linking them to supply chain resilience. [12] The goal of this study is to provide a comprehensive evaluation of the application of artificial intelligence (AI) in the value chain and food supply chain. It explores the concept of vertical integration within the food sector and examines how AI can be utilized at various stages of the food value and supply chain, while also identifying key barriers to its adoption. By reviewing and analyzing existing literature on this topic, the study aims to offer new insights, capture emerging research trends, and highlight promising areas of investigation.

The need for this research arises from the crucial role the agri-food industry plays in national development and its impact on the global economy. As the industry faces increasing competition, stakeholders in the food supply and value chain are motivated to explore innovative solutions and gain competitive advantages. Given the complexity of the food supply chain and the fragmented nature of earlier studies on different levels of the food system, this research seeks to provide a thorough overview of the integration of AI. [13] This study emphasizes how artificial intelligence (AI) can assist supply chains (SCs) in adapting to volatile environments and reduce costly decision-making for small and medium-sized enterprises (SMEs). Adopting a resource-based perspective, the research explores the impact of AI on SMEs' supply chain risk management. A structural model was developed and tested, incorporating AI-driven supply chain agility (SCA), supply chain reengineering, and risk management capabilities. Data was collected from executives, managers, and senior managers of SMEs, with analysis conducted using partial least squares-based structural equation modeling (PLS-SEM) and artificial neural networks (ANN).

The results reveal that using AI for risk management enhances supply chain reengineering capabilities and agility. Additionally, reengineering capabilities influence and mediate agility. A comparison of the PLS-SEM and ANN results showed consistency across models A and B. Given the current demand uncertainties in supply chain, managers face the challenge of making complex trade-offs under tight time constraints and limited resources, emphasizing the need for advanced AI-driven solutions. [14] This analysis reveals that Supply chain applications of Machine learning and artificial intelligence have garnered a lot of interest in both developed and developing countries. Most of the research is being conducted and published by countries that acknowledge the importance of the technological revolution. It also emphasizes the importance of collaboration between advanced and emerging economies to promote digital supply chain integration. In contrast, there is a significant lack of interest and engagement in many underdeveloped countries. [15] The increasing significance of humanitarian efforts underscores the need to address the challenges that exist in this sector. Issues Challenges such as delays, congestion, poor communication, and lack of accountability present opportunities to explore the potential advantages of emergency disruptive technologies. However, existing literature on humanitarian supply chains typically focuses on isolated technological applications and lacks a comprehensive framework for understanding these challenges and their solutions, a gap this article aims to fill. Through a case study of the 2007 Tabasco floods in Mexico, this research identifies solutions enabled by emergency disruptive technologies.

It argues that integrating multiple technologies is essential to realize meaningful improvements in humanitarian supply chains. This article proposes a framework that improves the flow of information, products, and financial resources by integrating three key technologies: artificial intelligence, block chain, as well as 3D printing. The analysis demonstrates how the framework may ease supply chain congestion, allow stakeholders to collaborate simultaneously, shorten lead times, and enhance resource transparency, traceability, and accountability. In addition, it enables affected individuals to actively participate in addressing their own needs. [16] Recent disruptions highlight the need to establish A robust and sustainable supply chain for manufacturing can be enhanced with Artificial intelligence (AI) holds promise, though further research is needed to understand how cloud adoption can enhance integration, collaboration, adaptability, and sustainable manufacturing practices. This study seeks to explore how the adoption of cloud technology and AI can boost resilience and sustainable performance by leveraging collaboration and adaptability capabilities within manufacturing organizations. [17] SCM, or supply chain management, which involves using technology and information to expand, design, implement, and monitor supply chain operations.

For SCM to be successful, it is crucial to guarantee a fluid flow of information at every stage, from raw material procurement to the transportation of finished goods. Machine learning (ML) systems and neural networks offer significant benefits to SCM. Techniques such as linear regression can help predict the bullwhip effect, while Random forest algorithms or decision trees can be useful with lead scoring, helping supply chain managers prioritize their efforts effectively. SCM uses big data and AI for tasks such as lead time planning and analyzing audio and video conversations between buyers and sellers. ML and SCM work in synergy to improve the efficiency of goods and service delivery. When used effectively, these technologies can save time and resources. In particular, the planning process can greatly benefit from extending and adapting established statistical methods with ML capabilities.



2. MATERIALS AND METHOD

Procurement:Procurement refers to the process of acquiring, purchasing, receiving, and evaluating all goods and services needed for business operations, from raw materials for production to software and office supplies.

Production:A society's physical resources, excluding people, comprise its means of production, involved in the production of goods and services. This includes natural resources, machinery, tools, offices, computers, stores, and distribution systems such as the Internet.

Inventory management:Inventory management involves managing a business's stock, which includes manufacturing, acquiring, storing, and selling products. It also includes managing raw materials, components, and finished goods within warehouses and during handling.

Distribution:The t-distribution is a statistical method used to represent data in which most observations are clustered around the mean, with fewer observations forming tails at either end. It The means of production in a society encompass all the physical components, excluding humans.

Transportation:Transportation involves the process of moving goods and people from one place to another through various methods. This movement is accomplished through various means of transport.

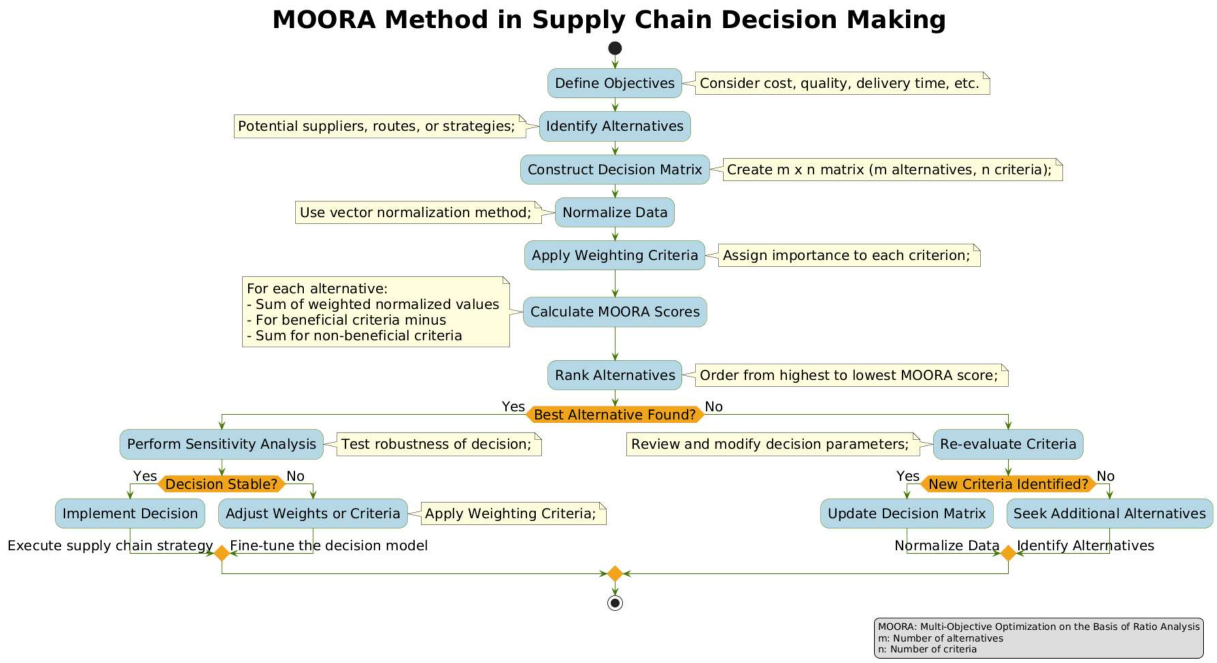
ANN:An artificial neural network (ANN) is a collection of fundamental, linked algorithms that process data in response to outside inputs. It is somewhat based on neural networks seen in biology. An ANN is structured in layers, with each layer consisting of interconnected nodes.

Rough set theory: A mathematical method for data analysis and decision-making in circumstances where the data is uncertain or incomplete. It serves as a tool for dealing with imperfect knowledge, including imprecise or inconsistent information.

Machine learning:Machine learning is a subset of artificial intelligence seeks to make it possible for computers and other machines to mimic human learning processes, carry out tasks on their own, and improve performance and accuracy through learning from experience and analyzing more data.

Expert system: A software application known as an expert system simulates the decisions and behaviors of an expert or organization with specialized expertise in a particular field by using artificial intelligence (AI) techniques.

Method: [18]This approach uses a matrix representing the responses of alternatives to different objectives, using ratios for these responses. To demonstrate its effectiveness, the MOORA method is compared with the established alternative reference point method and is shown to outperform other techniques. A unique feature of MOORA is the use of ratios, where the denominator It is the sum of the squared replies divided by the square root. These dimensionless ratios are either subtracted for minimization or added for maximizing. They have a range of zero to one, allowing for the ranking of alternatives. In addition, the method enables prioritization of specific objectives by replacing them with sub-objectives or by assigning importance coefficients. [19] This paper examines six decision-making scenarios, including the selection process involves Choosing a computerized numerical control (CNC) system, a flexible manufacturing system, or an industrial robot machine, a fast prototyping, non-traditional machining, and an automated inspection system designed for a particular mix of shape and material. Ineach case, the outcomes derived using the MOORA method closely align with those from earlier studies, demonstrating its relevance, efficiency, and versatility in tackling complex decision-making challenges in modern manufacturing



Systems. [20]These interpretations were tested through an application in the Lithuanian facilities sector. The multi-objective analysis took into account factors such as costs, experience and efficiency from the perspective of contractors, and quality, project duration and cost from the perspective of owners. Since these objectives are measured in different units, the dimensionless ratios of the MOORA method effectively addressed the normalization challenges. In the first stage of MOORA, these ratios were combined, and in the second stage, they were used as distances from a reference point. The results from both stages supported each other, serving as a robustness check. Furthermore, MOORA proved to be more reliable than other multi-objective optimization methods. For the Lithuanian facilities sector, both stages of MOORA were developed similar rankings, further validating the robustness of the results. [21] It should be noted that in order to address both advantageous and non-beneficial factors in decision-making teams, special normalization equations are occasionally needed. Nevertheless, a number of contemporary approaches are intricate and challenging to apply, frequently necessitating a high level of mathematical expertise.

This intricacy emphasizes the necessity of a straightforward, rational, and organized method for resolving material selection issues. Multi-objective optimization is one of three straightforward techniques that are used this paper relies on ratio analysis (MOORA), reference point method, and integer multiplication MOORA. These methods facilitate more accurate ranking of material alternatives while minimizing the impact of criterion weights and normalization processes. [22] The Multi-Objective Optimization by Ratio Analysis (MOORA) method fully satisfies the first six conditions. Furthermore, it partially satisfies the seventh condition by combining two different approaches to multi-objective optimization stands out as a very robust approach, as no other method has been proven to satisfy all seven conditions so effectively. [23] This research paper presents an analysis of a maintenance system using the MOORA method. The evaluation provides valuable insights that will help maintenance managers identify the most effective strategies to reduce operational costs due to machine failures and production line downtime. Ultimately, a complete evaluation of the maintenance system helps identify the best performing machines and guides the development of action plans to improve the performance of the underperforming machines. The MOORA method is mathematically simple, systematic, easy to understand, and well suited for maintenance system evaluation, providing a more objective and rational approach. For future research, it is recommended to explore other MCDM techniques to confirm the findings and compare the results under varying levels of decision-making uncertainty. [24] The following outcomes were obtained using the MOORA method: three contractors were placed in the top three, and the fourth contractor also received a favorable ranking.

One contractor was placed in the lowest category, and the remaining ten contractors were ranked lower, although their exact positions were not specified. Interestingly, the top performing contractors were not the most cost-effective, which was somewhat surprising. However, company size had a significant impact on the ranking. As a result, initial concerns about excluding small companies from consideration were found to be unfounded. [25] The MOORA method can be effectively utilized by management or decision-makers to make precise and timely decisions on various elements of the manufacturing environment, including product design, materials, manufacturing systems, facility location and organization, technology, and suppliers selection. However, since this method requires manual mathematical calculations, there is a need for a computer program to streamline the process and cut down on the computation time. Such a program can be created in the future using programming languages such as C++. [26]The ranking of performance factors is determined by six variables that influence three key aspects key components of a flexible manufacturing system (FMS): Productivity, flexibility, and quality are the key factors considered. The MOORA method is applied in three variations: ratio-based, reference point, and integer multiplication approaches. The rankings are made with and without considering attribute weights. In addition, the PSI method is employed to determine the most significant variable among the factors. The results from both the MOORA and PSI methods align, confirming that the production system's most important component is productivity. These rankings are further validated considering how consistently the outcomes from the various approaches used in this study. [27] Fuzzy AHP and Fuzzy MOORA methods were used to analyze data collected from surveys completed by industrial engineers and aspiring industrial engineers.

The objective of the study was to prioritize and rank job sectors in manufacturing, logistics, finance/banking, healthcare, technology, software/information, and education based on 10 criteria: pay, job satisfaction, career opportunities, productivity, goal orientation, status, guidance/pressure, social opportunities, job demand, and job ease. MOORA was selected over other multi-criteria decision-making (MCDM) methods for three main reasons. First, as a new MCDM approach, it was designed to overcome the limitations of older methods, enhancing their performance. Second, it reduces the computational time required for problem-solving, as noted in MCDM literature. Lastly, MOORA has minimal setup time and is widely recognized for its robustness, making it an appealing choice for this study. [28]To demonstrate the effectiveness of the proposed method, a material selection problem for a shaft was investigated. Using the fuzzy MOORA method, alloy steel was determined to be the best material for the shaft. To validate this approach for AHM material selection, it was compared with the fuzzy VIKOR, fuzzy GRA, and fuzzy TOPSIS methods. The strong alignment of the results from all four methods confirmed that the proposed approach is a reliable tool for solving AHM material selection problems. Then, the design and analysis of the main AHM components were completed, and based on these findings, the AHM was fabricated and tested to evaluate its performance.[29] Of the application concepts based on GRA, TM, PCA, GA, MOSA, MOPSO, and Taguchi, the MOORA method stands out for its simplicity, ease of use, and straightforward implementation.

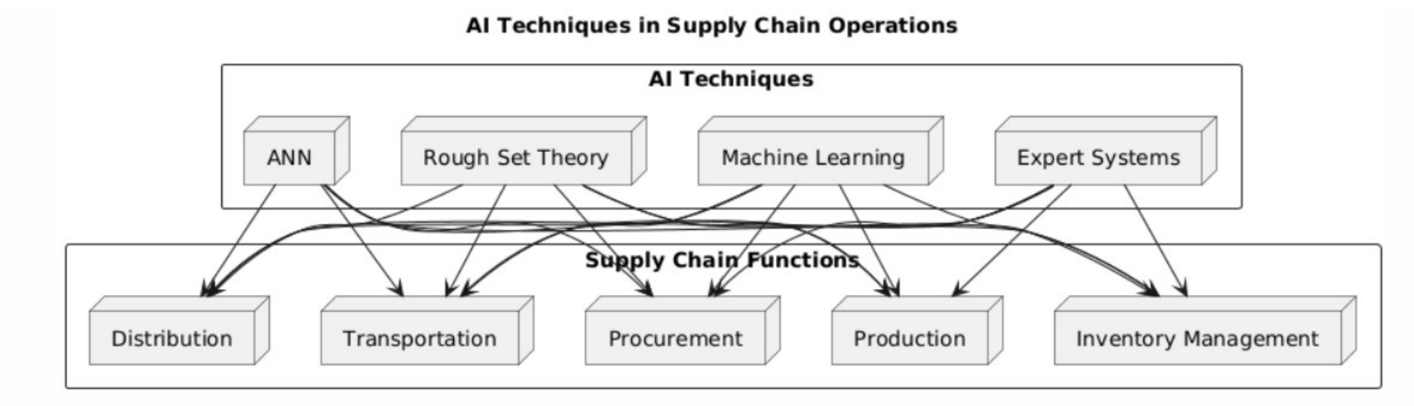
According to various researchers, MOORA provides solutions with accuracy comparable to or nearly identical to those obtained by more complex MODM techniques. By focusing only on direct ratio analysis, it requires minimal manual effort and basic mathematical calculations, which significantly reduces the computational time typically associated with more complex methods. Furthermore, while other techniques often require specialized software such as Minitab, Design Expert, or MATLAB, and advanced technical skills, the MOORA method can be effectively implemented using MS Excel. Its simplicity makes it an accessible and practical tool for both researchers and decision makers. [30] Selecting the most suitable ERP software from available market alternatives should be guided by a reliable MCDM approach. By using an MCDM-based approach improves the selection process by ensuring justification, accountability, and rationality, which are key factors for addressing complex and high-stakes decisions. This study introduces the fuzzy multi-objective optimization (MOORA) method, based on ratio analysis, and was used to determine the best ERP systems for two manufacturing companies. The results demonstrate that the fuzzy MOORA method is a straightforward, intuitive, and dependable tool for tackling decision-making challenges involving uncertain and imprecise valuation data.

3. ANALYSIS AND DISCUSSION

TABLE 1. Artificial Intelligence with Supply chain

	ANN	Rough set theory	Machine Learning	Expert System
procurement	38.00	51.00	36.00	68.00
Production	28.00	43.00	84.00	95.00
Inventory Management	96.00	97.00	63.00	76.00
Distribution	77.00	81.00	25.00	16.00
Transportation	80.00	60.00	35.00	43.00

The table1 compares the effectiveness of four artificial intelligence techniques—ANN (Artificial Neural Networks), Rough Set Theory, Machine Learning, and Expert System—across five supply chain functions: Procurement, Production, Inventory Management, Distribution, and Transportation. In Procurement, the Expert System scored the highest (68.00), suggesting it is most effective in this area, with ANN scoring the lowest at 38.00. For Production, the Expert System again performed the best (95.00), while Machine Learning (84.00) showed notable effectiveness as well, with ANN scoring the lowest at 28.00. In Inventory Management, Rough Set Theory (97.00) and ANN (96.00) had the highest scores, indicating their strength in managing inventory, while Expert System had a lower score of 76.00. In Distribution, Rough Set Theory (81.00) and ANN (77.00) outperformed others, with Machine Learning (25.00) performing poorly and Expert System at the lowest (16.00). Lastly, for Transportation, ANN (80.00) and Rough Set Theory (60.00) scored the highest, while Expert System scored 43.00. Overall, the Expert System is highly effective in Procurement and Production, while Rough Set Theory and ANN perform well in Inventory Management and Distribution, suggesting each AI technique is best suited to specific areas of the supply chain.



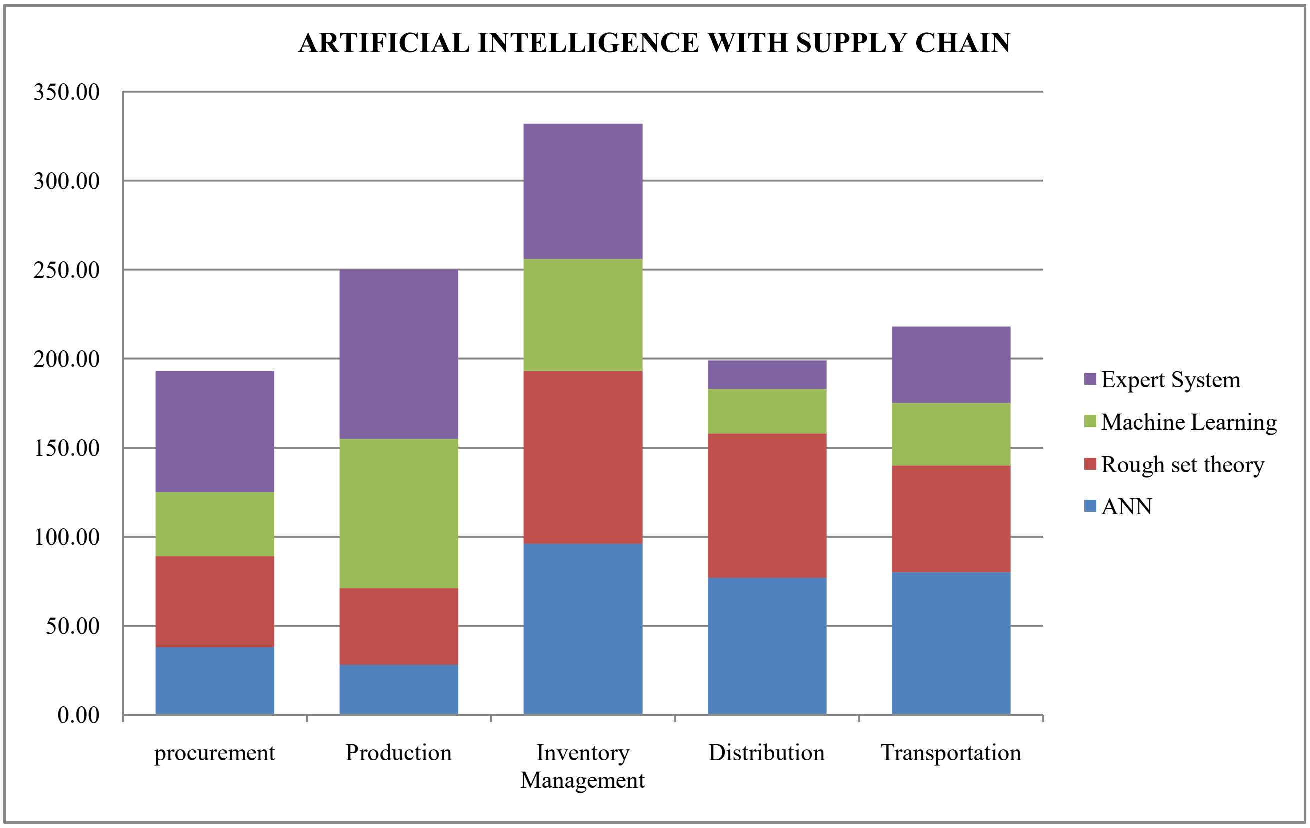


FIGURE 1. Artificial Intelligence with Supply Chain

Figure 1 illustrates the performance of various Artificial Intelligence techniques—ANN, Rough Set Theory, Machine Learning, and Expert Systems—across different supply chain functions. In procurement, Expert Systems score the highest at 68.00, while Machine Learning and ANN lag behind. In production, Expert Systems (95.00) lead, followed by Machine Learning (84.00). For inventory management, Rough Set Theory (97.00) and ANN (96.00) perform best, optimizing stock control. In distribution, Rough Set Theory (81.00) excels, while Expert Systems (16.00) perform poorly. Finally, in transportation, ANN (80.00) outperforms other techniques, aiding in route optimization and cost efficiency.

TABLE 2. Normalized Data

	Normalized Data		
ANN	Rough set theory	Machine Learning	Expert System
0.2464573	0.33	0.302	0.463
0.1816001	0.28	0.706	0.647
0.6226288	0.63	0.529	0.518
0.4994002	0.52	0.21	0.109
0.5188574	0.39	0.294	0.293

The table 2 presents the normalized data for four artificial intelligence techniques—ANN (Artificial Neural Networks), Rough Set Theory, Machine Learning, and Expert System—across five different variables or functions. In the first row, Expert System has the highest normalized value (0.463), followed by Rough Set Theory (0.33), Machine Learning (0.302), and ANN (0.2464573). This trend of Expert System performing strongly is consistent across most rows, with its

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values remaining relatively high in comparison to the others. For example, in the second row, Expert System leads with a value of 0.647, while Machine Learning (0.706) has the highest score in that particular row. Rough Set Theory also shows notable performance, particularly in the third row, where it holds the highest normalized value of 0.63, compared to 0.6226288 for ANN and 0.518 for Expert System. However, in the fourth row, Expert System shows the lowest value (0.109), while ANN (0.4994002) and Rough Set Theory (0.52) have stronger performances. Finally, in the fifth row, Expert System (0.293) and Machine Learning (0.294) show similarly low values, with Rough Set Theory at 0.39. This table highlights the varying strengths of these AI techniques depending on the specific function being evaluated.

TABLE 3. Weighted normalized DM

Weighted normalized DM				
procurement	0.061614	0.0823	0.0756	0.11586
Production	0.0454	0.0694	0.17641	0.16186
Inventory Management	0.155657	0.1565	0.13231	0.12949
Distribution	0.12485	0.1307	0.0525	0.02726
Transportation	0.129714	0.0968	0.0735	0.07326

The table 3 presents the weighted normalized decision matrix (DM) for four artificial intelligence techniques—ANN (Artificial Neural Networks), Rough Set Theory, Machine Learning, and Expert System—across five supply chain functions: Procurement, Production, Inventory Management, Distribution, and Transportation.In Procurement, the Expert System leads with the highest weighted normalized score of 0.11586, followed by Rough Set Theory (0.0823), Machine Learning (0.0756), and ANN (0.061614), indicating that the Expert System is most effective in procurement tasks. In Production, Machine Learning stands out with the highest score of 0.17641, closely followed by Expert System (0.16186), while Rough Set Theory and ANN have lower scores (0.0694 and 0.0454, respectively), demonstrating Machine Learning's strong performance in production-related tasks.For Inventory Management, Rough Set Theory slightly outperforms the others with a score of 0.1565, while ANN (0.155657) is also highly effective, with Expert System (0.12949) and Machine Learning (0.13231) showing slightly lower effectiveness. In Distribution, Rough Set Theory (0.1307) scores the highest, but Expert System (0.02726) performs poorly. Finally, in Transportation, ANN (0.129714) has the highest score, followed by Rough Set Theory, while Expert System and Machine Learning have nearly identical, and lower scores (0.07326 and 0.0735, respectively).Overall, the Expert System and Machine Learning show strengths in Procurement and Production, while Rough Set Theory excels in Inventory Management and Distribution.

TABLE 4.Assesment value

	Assesment value
procurement	-0.04758086
Production	-0.223507
Inventory Management	0.05033026
Distribution	0.17574558
Transportation	0.07973185

The table 4 presents the assessment values for various supply chain functions—Procurement, Production, Inventory Management, Distribution, and Transportation—across an unspecified set of factors. These assessment values indicate the overall performance or effectiveness of the AI techniques applied to each function.In Procurement, the negative assessment value of -0.04758086 suggests that the performance is slightly below an expected threshold or benchmark, indicating room for improvement. Production has a more significant negative assessment value of -0.223507, reflecting a notable gap in performance for this function, possibly signaling that improvements or alternative approaches are necessary.For Inventory Management, the positive assessment value of 0.05033026 indicates that the performance is slightly above the expected benchmark, suggesting that the AI techniques in use are relatively effective in this area. Similarly, Distribution shows a positive assessment value of 0.17574558, indicating good performance, which is encouraging for the AI techniques applied in this supply chain function.Finally, Transportation has a positive assessment value of 0.07973185, showing moderate effectiveness, though not as strong as Distribution. Overall, the assessment values highlight those AI techniques are performing well in Inventory Management, Distribution, and Transportation but require adjustments or enhancements for Procurement and Production.

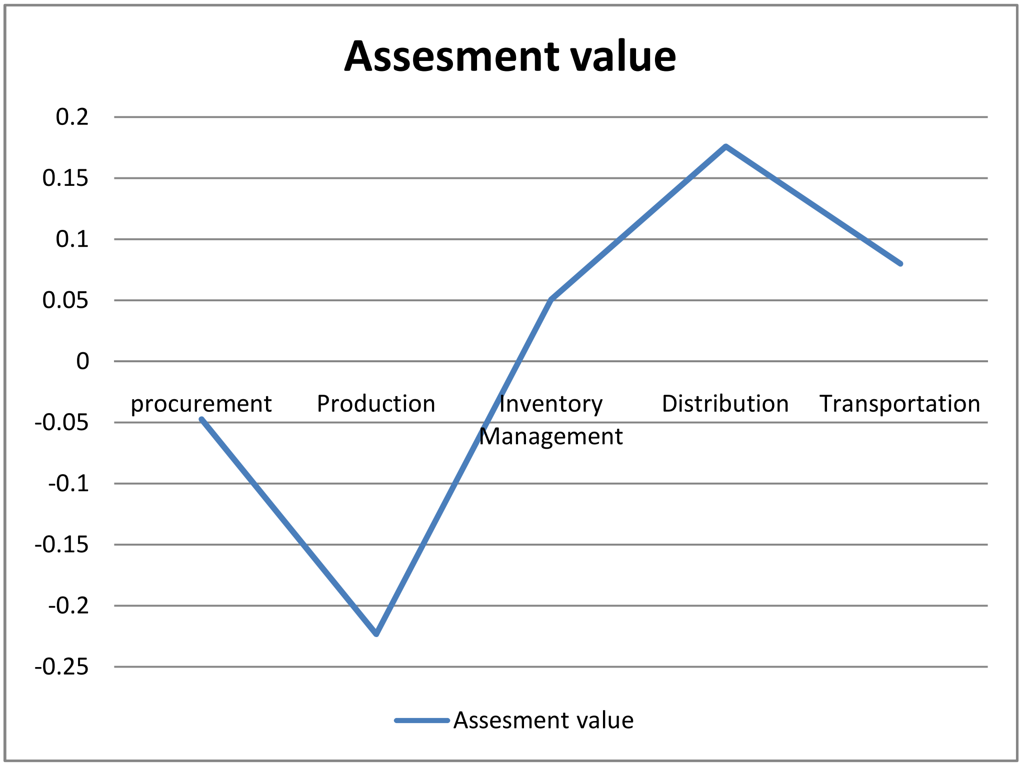

FIGURE 2.Assesment value

Figure 2 presents the assessment values for various supply chain functions, reflecting the impact of AI techniques. Procurement has a negative value of -0.04758086, indicating a slight decrease in efficiency or performance. Production shows a more significant negative assessment value of -0.223507, suggesting a potential area of improvement. In contrast, inventory management has a positive assessment value of 0.05033026, indicating improved performance. Distribution scores the highest with 0.17574558, showing a notable positive impact, while transportation also demonstrates a positive value of 0.07973185, reflecting enhanced performance. These values suggest differing levels of AI effectiveness across different supply chain stages.

TABLE 5. Rank

	Rank
procurement	4
Production	5
Inventory Management	3
Distribution	1
Transportation	2

The table 5 presents the rankings of Different supply chain functions, Procurement, Production, Inventory Control, and Distribution and Transportation—based on the performance of artificial intelligence techniques. These rankings provide a comparative assessment of the effectiveness of AI in each area.Distribution ranks first (1), indicating that AI techniques are most effective in this function compared to others. This suggests that the AI approaches applied to Distribution are optimized and yield the best results. Transportation ranks second (2), indicating a strong performance but slightly less effective than Distribution. AI techniques for Transportation show good results, though there may still be room for improvement to match Distribution's effectiveness.Inventory Management ranks third (3), suggesting that AI techniques are moderately effective in this area, with positive performance but not as strong as Distribution or Transportation. Procurementranks fourth (4), indicating that AI methods in this function are less effective relative to the others, possibly due to challenges in adapting AI to this domain or room for further optimization. Finally, Productionranks fifth (5), the lowest, which implies that AI techniques in this function are underperforming compared to others, possibly due to the complexity or specific requirements of production processes that AI has not fully addressed.

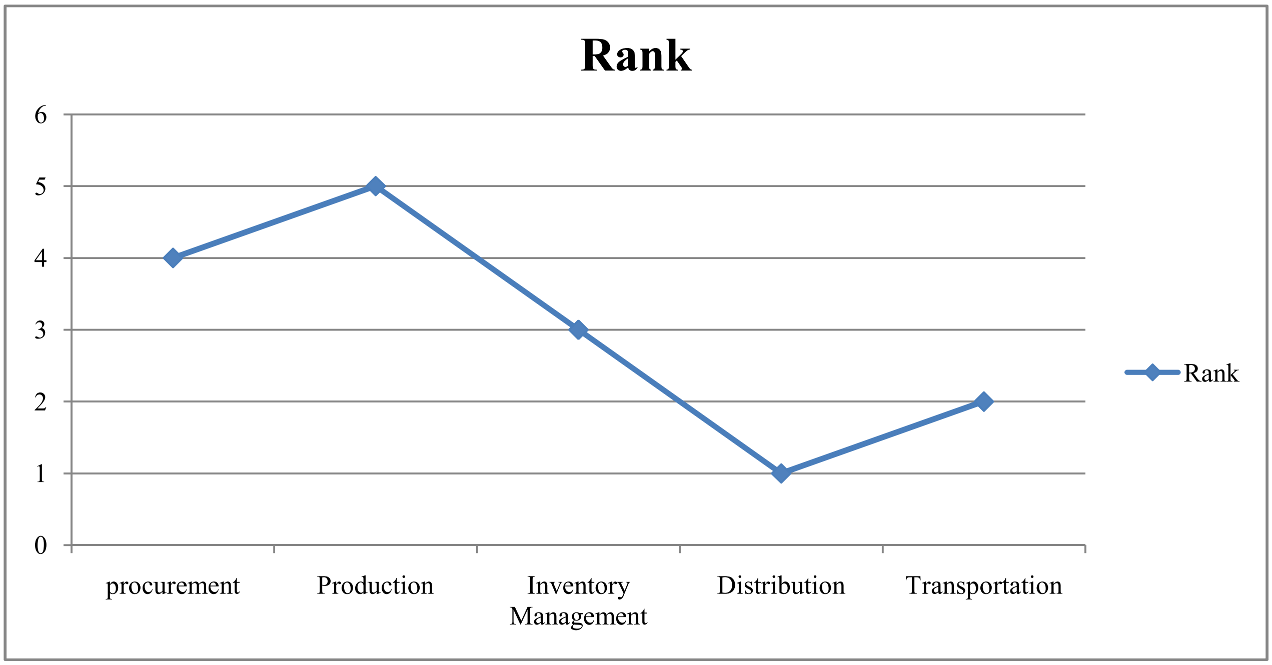

FIGURE 3.Rank

Figure 3 shows the rankings of supply chain functions based on their effectiveness in utilizing AI techniques. In procurement, the function ranks 4th, indicating a moderate impact of AI techniques on improving procurement processes. Production ranks 5th, suggesting there is room for greater AI optimization in production. Inventory management ranks 3rd, reflecting a strong but not the highest level of AI impact. Distribution, ranking 1st, shows the greatest improvement from AI techniques, demonstrating the significant benefits of AI in optimizing distribution operations. Transportation ranks 2nd, indicating AI's substantial contribution to improving transportation efficiency and route planning.

4. Conclusion

In summary, the difficulties and interruptions brought induced by the most recent pandemic, coupled with the rapid pace of globalization and evolving customer demands, underscore the urgent need for resilience in supply chain systems. Incorporating Cutting-Edge Technologies like Artificial Intelligence (Ai) offers valuable opportunities to address these challenges by improving supply chain efficiency, fostering collaboration, and refining decision-making. Research from multiple studies highlights AI function in risk management forecasting and optimization in providing innovative solutions to reduce volatility and uncertainty. Furthermore, approaches such as the MOORA method provide structured frameworks for addressing multi-objective optimization challenges in supply chain management and other areas. Future research should aim to combine AI with decision-making tools such as MOORA to develop comprehensive, scalable, and efficient solutions tailored to different industries and regions. In addition, bridging the digital divide and promoting the global adoption of these technologies will be crucial to reducing inequality and fostering sustainable growth in supply chain networks. Distribution ranks first, demonstrating the most significant improvement from AI techniques, while manufacturing ranks fifth, indicating the potential for further AI optimization in this sector.

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