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REVIEW ARTICLE

AI-Driven Supplier Selection Using AHP and TOPSIS Approaches for Optimized Supply Chain Management

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ABSTRACT:

In the modern globalized and digitally connected marketplace, the selection of suitable contractors is a critical strategic decision with far-reaching implications across the supply chain. Conventional supplier evaluation methods, though beneficial, often prove inadequate when dealing with ambiguity, scarce information, and subjective inputs. Incorporating artificial intelligence into these processes can significantly improve the efficiency, accuracy, and responsiveness of decision- making. This research explores the integration of AI with established supplier selection models namely AHP and TOPSIS, to offer supply chain managers a robust framework for comparative assessment and enhanced strategic choices. Application of AI to AHP and TOPSIS results in more adaptive, data-driven evaluations that strengthen strategic sourcing decisions in dynamic supply chain environments; and the ability to process complex datasets and generate optimized supplier rankings with greater reliability and speed.

KEYWORDS: Supplier Selection, AHP, TOPSIS

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1. INTRODUCTION

Globalization, digital transformation, and increasing market competition have significantly increased the complexity of supply chain management. Organizations are required to select suppliers capable of delivering high-quality products at competitive prices while maintaining reliability, sustainability, and operational flexibility. Supplier selection therefore represents one of the most critical strategic decisions affecting manufacturing performance, customer satisfaction, and long-term organizational success.[1–3]

Traditional supplier evaluation primarily relied on cost-based comparisons. However, modern supply chains require decision-makers to simultaneously consider numerous qualitative and quantitative criteria including quality, delivery reliability, production capability, technological innovation, environmental sustainability, financial stability, and risk management. The presence of multiple

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conflicting criteria makes supplier selection a challenging multi-criteria decision-making (MCDM) problem.[4]

Among various MCDM techniques, the **Analytical Hierarchy Process (AHP)** and the **Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)** are widely recognized for their effectiveness in evaluating complex decision problems involving multiple alternatives and criteria. AHP determines the relative importance of decision criteria through pairwise comparisons, whereas TOPSIS ranks alternatives according to their distance from ideal and negative-ideal solutions. Together, these methods provide a systematic framework for supplier evaluation and ranking.[5–7]

Although AHP and TOPSIS have demonstrated considerable success, conventional implementations largely depend on expert judgement and manually collected information. Human evaluations are often influenced by uncertainty, inconsistency, incomplete information, and subjective preferences, reducing the reliability of supplier rankings. In rapidly changing supply chain environments, manual evaluation methods also struggle to process large volumes of operational data in real time.[8]

Artificial Intelligence (AI) has emerged as a transformative technology capable of overcoming many of these limitations. AI integrates machine learning, deep learning, natural language processing, optimization algorithms, and predictive analytics to automate complex decision-making processes. By analysing historical procurement records, supplier performance indicators, logistics information, customer feedback, financial reports, and market trends, AI systems generate objective supplier evaluations with significantly greater speed and accuracy than conventional approaches.[9]

The integration of AI with AHP and TOPSIS creates an intelligent supplier selection framework in which machine learning algorithms automatically identify important decision criteria, estimate criterion weights, process real-time supplier information, and continuously update supplier rankings based on changing business environments. This adaptive capability enables organizations to improve procurement efficiency while reducing risks associated with supplier failure, quality variation, and supply chain disruptions.[10]

Recent developments in **Industry 4.0**, cloud computing, Internet of Things (IoT), blockchain technology, and big data analytics have further accelerated the adoption of AI-based supplier management systems. Digital supply chains generate enormous amounts of operational data that can be analysed using AI algorithms to predict supplier performance, identify procurement risks, optimize sourcing strategies, and improve supply chain resilience.[11]

The COVID-19 pandemic highlighted the importance of resilient supplier networks capable of responding rapidly to unexpected disruptions. AI-assisted supplier evaluation has therefore gained considerable attention because it enables organizations to continuously monitor supplier performance and identify potential risks before operational failures occur. Predictive supplier analytics have become an essential component of modern strategic sourcing and procurement management.[12]

The objective of this review is to examine recent developments in AI-driven supplier selection using AHP and TOPSIS approaches. The review discusses the theoretical principles of these decision-making techniques, recent AI integration strategies, industrial applications, benefits, challenges, and future research directions associated with intelligent supplier evaluation systems.

2. ARTIFICIAL INTELLIGENCE IN SUPPLIER SELECTION

Artificial Intelligence has fundamentally transformed procurement and supplier management by enabling organizations to analyse large and complex datasets beyond the capabilities of traditional decision-making methods. AI algorithms continuously learn from historical procurement records, supplier databases, market conditions, logistics information, and operational performance to generate more accurate supplier evaluations.[13]

Machine learning techniques identify hidden relationships among supplier performance indicators that may not be apparent using conventional

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statistical analysis. Predictive models estimate future supplier reliability, delivery performance, production capacity, financial stability, and risk levels, enabling proactive procurement planning.

The major AI technologies applied in supplier selection include:

- Machine Learning (ML)
- Deep Learning (DL)
- Artificial Neural Networks (ANN)
- Natural Language Processing (NLP)
- Fuzzy Artificial Intelligence
- Expert Systems
- Reinforcement Learning
- Evolutionary Algorithms

These technologies improve supplier evaluation by reducing human bias, processing uncertain information, and providing continuous decision support based on real-time operational data.[14]

2.1 AI-Based Decision Support Systems

Modern procurement systems increasingly employ AI-powered decision support platforms capable of integrating information from Enterprise Resource Planning (ERP) systems, supplier databases, logistics networks, financial reports, and customer feedback.

AI decision support systems perform:

- Automatic supplier screening
- Performance prediction
- Risk assessment
- Cost optimization
- Sustainability evaluation
- Contract recommendation
- Supplier ranking

These intelligent systems significantly reduce procurement cycle time while improving decision consistency.

2.2 AI and Sustainable Supplier Management

Environmental sustainability has become an important supplier selection criterion. AI enables organizations to evaluate suppliers according to carbon emissions, resource efficiency, waste management, regulatory compliance, and environmental certifications.

Machine learning algorithms analyse environmental performance indicators alongside traditional economic criteria to support sustainable procurement decisions that align with Environmental, Social, and Governance (ESG) objectives.

Table 1. Major AI Applications in Supplier Selection

AI Technology	Supply Chain Application
Machine Learning	Supplier performance prediction
Neural Networks	Demand forecasting
Natural Language Processing	Contract analysis
Expert Systems	Procurement recommendations
Deep Learning	Supplier risk assessment
Reinforcement Learning	Dynamic supplier optimization
Big Data Analytics	Performance evaluation

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3. ANALYTICAL HIERARCHY PROCESS (AHP)

The **Analytical Hierarchy Process (AHP)**, developed by Thomas L. Saaty, is one of the most widely adopted Multi-Criteria Decision-Making (MCDM) techniques for supplier evaluation. AHP decomposes a complex decision problem into a hierarchical structure consisting of the overall objective, evaluation criteria, sub-criteria, and decision alternatives. Through systematic pairwise comparisons, decision-makers quantify the relative importance of each criterion and determine the overall ranking of suppliers.[16]

In supplier selection, AHP enables procurement managers to evaluate suppliers simultaneously across multiple conflicting criteria such as cost, quality, delivery performance, flexibility, technological capability, sustainability, financial stability, and after-sales support. The structured hierarchy simplifies complex decision-making and improves transparency while reducing subjective bias.[17]

The typical hierarchy consists of three levels:

- **Level 1:** Goal (Selection of the Best Supplier)
- **Level 2:** Evaluation Criteria
- **Level 3:** Alternative Suppliers

3.1 Pairwise Comparison Matrix

The relative importance of criteria is determined using Saaty's nine-point preference scale. Pairwise comparisons generate a reciprocal matrix:

$$A=[a_{ij}]$$

where

- (a_{ij})=importance of criterion (i) relative to criterion (j)

The reciprocal property is

$$a_{ji}=\frac{1}{a_{ij}}$$

The principal eigenvector of the comparison matrix provides the normalized weight of each criterion.

3.2 Consistency Evaluation

Decision consistency is verified using the **Consistency Index (CI)**

$$CI=\frac{\lambda_{max}-n}{n-1}$$

where

- (λ_{max})=maximum eigenvalue
- (n)=number of criteria

The **Consistency Ratio (CR)** is calculated as

$$CR=\frac{CI}{RI}$$

where RI represents the Random Index.

Generally,

$$CR<0.10$$

indicates acceptable judgement consistency.[18]

Table 2. Typical Supplier Selection Criteria

Criterion	**Importance**
Cost	High
Product Quality	Very High
Delivery Reliability	Very High
Production Capacity	High
Financial Stability	Medium
Sustainability	High
Technological Capability	High
Service Support	Medium

4. TECHNIQUE FOR ORDER PREFERENCE BY SIMILARITY TO IDEAL SOLUTION (TOPSIS)

TOPSIS is another widely used MCDM method introduced by Ching-Lai Hwang and Kwangsun Yoon. Unlike AHP, TOPSIS ranks alternatives by measuring their geometric distance from an ideal solution and a negative-ideal solution.[19]

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The preferred supplier should possess the shortest distance from the positive ideal solution while maintaining the greatest distance from the negative ideal solution.

4.1 Decision Matrix

The supplier evaluation matrix is represented as

$$X=[x_{ij}]$$

where

- (x_{ij})=performance of supplier (i) under criterion (j).

4.2 Normalization

The normalized matrix is calculated using

$$r_{ij}=\frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}x_{ij}^{2}}}$$

This eliminates dimensional differences among evaluation criteria.

4.3 Weighted Normalized Matrix

The weighted values are

$$v_{ij}=w_jr_{ij}$$

where

- (w_j)=criterion weight obtained from AHP.

4.4 Ideal Solutions

Positive Ideal Solution

$$A^{+}=\{v_1^{+},v_2^{+},...,v_n^{+}\}$$

Negative Ideal Solution

$$A^{-}=\{v_1^{-},v_2^{-},...,v_n^{-}\}$$

4.5 Separation Measures

Distance from the ideal solution

$$S_i^{+}=\sqrt{\sum(v_{ij}-v_j^{+})^{2}}$$

Distance from the negative ideal solution

$$S_i^{-}=\sqrt{\sum(v_{ij}-v_j^{-})^{2}}$$

4.6 Relative Closeness

Supplier ranking is determined using

$$C_i=\frac{S_i^{-}}{S_i^{+}+S_i^{-}}$$

The supplier with the highest value of (C_i) is considered the most suitable procurement choice.[20]

5. AI-INTEGRATED AHP–TOPSIS FRAMEWORK

Artificial Intelligence significantly enhances traditional AHP and TOPSIS by automating data collection, reducing subjective judgement, and continuously updating supplier rankings based on real-time information. Instead of relying solely on expert opinions, AI algorithms analyse procurement databases, supplier performance records, enterprise resource planning (ERP) systems, logistics information, financial reports, and customer feedback to generate objective evaluation scores.[21]

Machine learning models automatically identify influential decision criteria and estimate criterion weights using historical procurement outcomes. These AI-generated weights can subsequently be incorporated into AHP, while TOPSIS performs the final supplier ranking. The integration enables procurement systems to respond dynamically to changing supplier performance and market conditions.

5.1 AI Workflow

The AI-driven supplier selection process consists of:

1. Data acquisition from ERP, IoT, and supplier databases.
2. Data preprocessing and normalization.

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3. Feature extraction using machine learning.
4. Automatic criteria weighting using AI.
5. AHP consistency analysis.
6. TOPSIS ranking.
7. Decision support and supplier recommendation.

This framework minimizes manual intervention while improving decision speed and reliability.[22]

5.2 Applications in Procurement

AI-assisted AHP–TOPSIS has been successfully applied in:

- Manufacturing supplier selection
- Automotive procurement
- Healthcare supply chains
- Construction contractor evaluation
- Sustainable supplier assessment
- Vendor risk management
- Green procurement
- Global sourcing strategies

The integration of AI enables continuous supplier monitoring and adaptive decision-making, improving procurement efficiency and resilience.[23]

6. BENEFITS OF AI-DRIVEN SUPPLIER SELECTION

Artificial Intelligence has significantly improved supplier evaluation by enabling intelligent data processing, predictive analytics, and automated decision-making. The integration of AI with AHP and TOPSIS overcomes the limitations of conventional supplier assessment methods, leading to faster, more reliable, and objective procurement decisions.

6.1 Improved Decision Accuracy

AI algorithms analyse large volumes of procurement, logistics, financial, and operational data to generate objective supplier evaluations. Unlike conventional approaches that rely heavily on human judgement, AI minimizes subjective bias and improves consistency in supplier ranking.[31]

6.2 Faster Procurement Decisions

Manual supplier evaluation is often time-consuming due to extensive data collection and pairwise comparisons. AI automates data acquisition, preprocessing, criteria weighting, and supplier ranking, thereby substantially reducing procurement cycle time and enabling rapid strategic decision-making.

6.3 Dynamic Supplier Evaluation

Supplier performance continuously changes because of fluctuations in production capacity, transportation delays, market conditions, and financial stability. AI systems continuously monitor supplier performance using real-time operational data and automatically update supplier rankings whenever significant changes occur.[32]

6.4 Risk Prediction

Machine learning algorithms can predict supplier-related risks including:

- Delivery delays
- Financial instability
- Production disruptions
- Quality deviations
- Inventory shortages
- Supply chain interruptions

Early identification of these risks enables organizations to implement preventive procurement strategies and improve supply chain resilience.

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6.5 Sustainable Procurement

AI facilitates sustainable supplier selection by incorporating environmental, social, and governance (ESG) indicators into the evaluation process. Parameters such as carbon emissions, energy consumption, waste management, recycling practices, environmental certifications, and regulatory compliance can be simultaneously analysed with traditional economic criteria, supporting green supply chain management.[33]

Table 3. Benefits of AI-Based Supplier Selection

Feature	Benefit
Machine Learning	Predictive supplier evaluation
AHP	Objective criteria weighting
TOPSIS	Reliable supplier ranking
Big Data Analytics	Real-time decision support
Cloud Computing	Faster information processing
AI Automation	Reduced procurement time
ESG Analytics	Sustainable supplier selection

7. CHALLENGES AND LIMITATIONS

Despite considerable advantages, AI-assisted supplier selection presents several technical and organizational challenges.

7.1 Data Availability and Quality

AI models require large volumes of high-quality procurement data. Missing, inconsistent, or inaccurate supplier information may reduce model accuracy and produce unreliable rankings. Data standardization remains a significant challenge in global supply chains.[34]

7.2 Model Transparency

Many AI algorithms, particularly deep learning models, operate as "black-box" systems, making it difficult for procurement managers to understand how supplier rankings are generated. Explainable Artificial Intelligence (XAI) is increasingly important for improving transparency and trust in AI-assisted decision-making.[35]

7.3 Cybersecurity and Data Privacy

Modern procurement systems frequently utilize cloud computing and digital supplier databases. Protecting confidential procurement information, supplier contracts, and financial records from cyberattacks requires robust cybersecurity frameworks, encryption techniques, and access control mechanisms.

7.4 Integration with Existing ERP Systems

Organizations often use diverse Enterprise Resource Planning (ERP) platforms and supplier management systems. Integrating AI algorithms with existing digital infrastructure may require significant investment, technical expertise, and organizational change management.

7.5 Human Decision-Making Remains Essential

Although AI substantially improves supplier evaluation, final procurement decisions should continue to involve experienced managers. Human expertise remains essential for considering strategic partnerships, negotiation capabilities, ethical issues, geopolitical risks, and long-term organizational objectives that may not be fully captured by AI algorithms.

8. FUTURE PERSPECTIVES

Future AI-driven supplier selection systems are expected to become increasingly autonomous,

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adaptive, and intelligent. Emerging technologies such as Explainable Artificial Intelligence (XAI), Generative AI, blockchain, Digital Twins, cloud computing, and the Industrial Internet of Things (IIoT) will further enhance procurement decision-making.

Future research directions include:

- AI-enabled autonomous procurement systems
- Blockchain-supported supplier verification
- Explainable AI for transparent supplier ranking
- Real-time supplier monitoring using IoT
- Integration with Digital Twin-based supply chains
- Generative AI for procurement strategy optimization
- Deep learning for supplier risk forecasting
- Sustainable and circular supply chain evaluation

The convergence of AI with Industry 5.0 is expected to create intelligent procurement ecosystems capable of continuously learning, adapting, and optimizing sourcing decisions while enhancing resilience, sustainability, and global competitiveness.[36]

9. CONCLUSION

Supplier selection is a critical strategic activity that directly influences supply chain performance, operational efficiency, and organizational competitiveness. The integration of Artificial Intelligence with established Multi-Criteria Decision-Making techniques such as AHP and TOPSIS provides a robust framework for objective, adaptive, and data-driven supplier evaluation. AI enhances conventional decision-making by automating data processing, improving criteria weighting, predicting supplier performance, and continuously updating supplier rankings based on real-time information. The combined AI–AHP–TOPSIS approach improves decision accuracy, reduces human bias, accelerates procurement processes, and supports sustainable sourcing practices. Although challenges related to data quality, cybersecurity, model transparency, and system integration remain, continued advancements in machine learning, big data analytics, blockchain, and Industry 4.0 technologies are expected to further strengthen intelligent supplier management systems. Overall, AI-driven supplier selection represents a promising approach for developing resilient, efficient, and sustainable supply chains.

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