

Decision Support Systems in Electronic Procurement for Public Sector Procurement: A Systematic Literature Review on Machine Learning Integration

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Received : Feb 26, 2026; Revised : Mar 13, 2026; Accepted : Mar 13, 2026; Published : Apr 18, 2026

Abstract

This study analyzes the evolution of Decision Support Systems (DSS) and Multi-Criteria Decision Making (MCDM) in public sector procurement between 2020 and 2025. Using bibliometric analysis of Scopus and Web of Science articles, the research focuses on themes such as e-procurement, supplier selection, public procurement, and the integration of intelligent technology. Network visualization, overlays, and density mapping were applied to explore keyword relationships, temporal trends, and research intensity. Findings reveal that in 2020, studies concentrated on transparency and digitalization in public e-procurement, with classical MCDA methods, fuzzy TOPSIS, and semantic DSS dominating the approaches. By 2022–2023, the emphasis shifted toward intelligent technologies, including artificial intelligence, neuro-fuzzy systems, and data mining algorithms. These innovations expanded DSS functions from evaluation to predictive analytics and optimization. Core themes such as supplier selection, optimization, and public procurement remained central, while emerging topics like sustainability and clinical decision support systems pointed to new research directions. A significant gap was identified in the university context. Although public sector e-procurement has been widely studied, no research has specifically addressed DSS–MCDM applications in higher education procurement systems. Consequently, future agendas should prioritize adaptive DSS tailored to universities, blockchain integration for transparency, and AI applications in clinical and humanitarian systems.

Keywords : *Decision Support Systems, Multi-Criteria Decision Making, Procurement, Artificial Intelligence, Blockchain, Sustainability*

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1. INTRODUCTION

Procurement in Higher Education is a crucial strategic function, given that universities operate as public sectors that manage state and community funds. [1]. This urgency stems from the volume and variety of needs that must be met, ranging from high-tech laboratory equipment and IT hardware to academic e-resources, which directly support the tridharma of universities: education, research, and community service.[1] [2][3]. Efficiency in the procurement process, including speed, cost savings, and effective inventory management, is crucial for ensuring that academic resources are available on time, thereby avoiding hindrances to research productivity and teaching quality [2]. Therefore, e-procurement in universities is no longer just an administrative transaction, but a primary enabler for the achievement of institutional goals. [4].

In addition to efficiency, the need for high accountability in the procurement of Higher education institutions is very urgent due to their status as a public entity subject to strict supervision [3]. Every tender decision and procurement transaction should be based on the principles of transparency, fairness, and regulatory compliance [3][4] [5]. The risk of fraud, collusion, and waste of public funds is a real threat that can damage the reputation and academic integrity of institutions [6] [7] [8] [2]. The use of Decision Support Systems (DSS) and advanced e-tendering technologies, especially those supported by predictive analytics, is urgently needed to mitigate these risks [2]. Thus, a modern procurement system

must be able to provide a comprehensive audit trail and objective decision-making tools, ensuring that every rupiah of the Higher education institution's budget is spent wisely and accountably [9].

Despite digitalization efforts, traditional procurement systems, especially in the public sector, such as Universities, still face inherent vulnerabilities to fraudulent practices and collusion. [10]. In a manual or e-tendering process with minimal analytical supervision, high human intervention gaps allow for bid manipulation, the determination of specifications that favor certain vendors (tailoring), and the leakage of bid price information. This vulnerability not only impacts cost overruns and inefficient budget allocation but also fundamentally undermines the principles of transparency and fair competition that institutions using public funds must uphold [11]. As a result, the potential for public financial losses becomes enormous, while the integrity of the overall procurement process is in doubt.

In addition to the threat of fraud, traditional procurement in Higher Education is also highly vulnerable to the risk of poor vendor performance and contract non-compliance [5] [12] [10]. In traditional schemes, vendor evaluations are often based on limited criteria (especially price and basic qualifications) without involving an in-depth analysis of historical data regarding product quality, delivery delays, or prior ethical compliance. [13]. When vendors with poor performance are selected, it will directly hinder the university's operations, for example, by causing delays in the delivery of vital research equipment or the supply of goods that do not meet specifications. [14]. The long-term consequences include reputational losses for the College, disruption to academic activities, and additional costs for the maintenance or replacement of goods [2]. Therefore, a shift from reactive processes to predictive systems for risk mitigation [15].

The widespread adoption of E-Tendering and E-Procurement in the public sector, including Higher Education, has been a significant leap in efforts to improve procurement transparency and efficiency [2]. By transitioning the tender process from a manual mechanism to a digital platform, the system generates a detailed and accessible audit trail, thereby reducing direct contact that could potentially fuel corruption and ensuring that tender information is disseminated fairly to all interested parties [8] [6]. The use of this electronic system can standardize procedures, shorten the procurement cycle, and ultimately enhance the governance of procurement for goods [15]. This digital recording of transactions has resulted in significant and continuous volumes of data, altering the nature of the challenges faced by system managers [16] [17].

Although E-Procurement offers structural transparency, the system now generates a considerable volume of transaction data (Big Data) that records every interaction, offer, and performance history of vendors. [18]. This data, although abundant, is often not fully utilized if it is only analyzed using traditional statistical or descriptive methods. [19]. Extracting the actual value of this Big Data especially to identify complex collusion patterns, hidden price anomalies, or early signals of risk requires much more sophisticated analysis. [20]. Therefore, the need to integrate Machine Learning (ML) based Decision Support System (DSS) tools is crucial [7] [8]. This advanced analysis enables universities to transition from merely recording transactions to leveraging data for strategic prediction and optimization, a fundamental prerequisite for navigating modern procurement dynamics. [2].

Decision Support Systems (DSS) are designed to provide a solution that supports data-driven decision-making, reduces subjectivity, and enhances accountability. The integration of DSS with machine learning enables the analysis of historical data, vendor performance predictions, and the optimization of tender processes. This article aims to identify DSS research trends in college e-procurement, analyze the integration of ML in vendor selection, and present future research directions to support sustainable procurement governance

2. METHOD

2.1. Research Design

This study employs a systematic literature review approach, focusing on the identification, interpretation, evaluation, and classification of all articles related to pre-defined research questions. In contrast to conventional literature reviews, which primarily focus on descriptive findings in a specific area of knowledge, systematic literature reviews provide a more comprehensive and valuable picture of the research discipline. [9].

2.2. Search Protocol

The initial search process utilizes Scopus, combining a set of keywords with Boolean operators (ANDs, ORs) to target a specific slice of the research topic precisely. The search logic is built around four core components of research: DSS/ML, E-Procurement/E-Tendering, and Vendor Selection. The main search combinations used are: ("Decision Support System" OR DSS) AND ("Machine Learning" OR ML) AND ("E-Tendering" OR "E-Procurement" OR Procurement) AND ("vendor selection" OR "supplier selection"). Initial steps using search combinations ("Decision Support System" OR DSS) AND ("Machine Learning" OR ML) AND ("E-Tendering" OR "E-Procurement" OR Procurement) dan ("Machine Learning" OR ML) AND ("E-Tendering" OR "E-Procurement" OR Procurement) AND ("vendor selection" OR "supplier selection").

2.3. Inclusion and Exclusion Criteria

The literature screening process establishes strict inclusion criteria to guarantee the quality and relevance of the findings. The main criterion is that the article must be published in a peer-reviewed journal in a reputable international journal that is indexed in Scopus. Thematically, the literature should explicitly discuss the integration of Decision Support Systems (DSS) or Machine Learning (ML) in the context of E-Procurement or E-Tendering.

Instead, exclusion criteria are applied to eliminate literature that has a low scientific impact or falls outside the scope of the research. In addition, studies that focus too broadly or discuss physical/traditional procurement without utilizing electronic platforms or advanced analytical models were also published, with limited exclusion in the fields of computer science, engineering, mathematics, business, management, accounting, and decision sciences. This exclusion enables SLR to focus on the dynamics of digital transformation and data-driven predictive solutions in modern procurement, thereby addressing defined research gaps and enhancing its analytical acumen.

2.4. Data Selection and Extraction Process

The first stage of the data selection and extraction process in a Systematic Literature Review (SLR) is Initial Identification, which is carried out as soon as the search protocol is executed on the selected academic databases (Scopus, Springer, and IEEE Xplore). At this stage, all search results generated by a combination of keywords and Boolean operators are collected, and duplicate articles are eliminated. The initial screening process is then focused on assessing suitability based on the title and abstract of each article. This assessment is conservative, where the article is considered potential and proceeds to the next stage if the title contains a key phrase (e.g., Machine Learning, DSS, Procurement, Higher Education) or the abstract indicates that the study addresses predictive models or vendor selection in the context of electronic procurement.

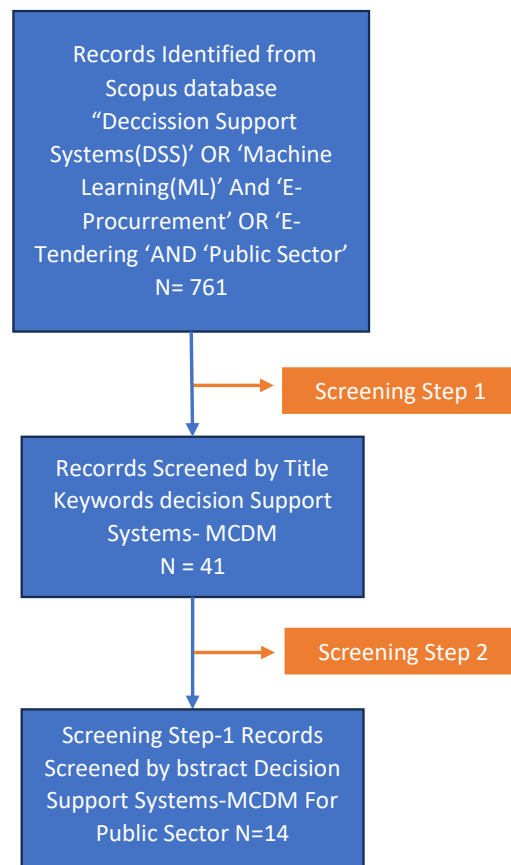


Figure 1. Proses Screening

3. RESULT

3.1. Screening Process

The initial process found 761 articles. After the filter for the year (2020-2025), the title and abstract generated 41 articles. After a comprehensive evaluation based on scientific fields including computer science, business, management, accounting, decision sciences, 14 final articles were produced for analysis.

3.2. Bibliometric Analysis

The number of publications published in 2020 was dominated by seven publications, focusing on the fuzzy method of TOPSIS, MCDA, and the development of e-tendering/e-government DSS. Focus on public transparency and tender optimization. In 2022, there were three publications on game theory for price negotiation, the Best-Worst Method (BWM), and neuro-fuzzy for predicting procurement success. The trend is shifting to strategic and predictive optimization.

In 2023, there were two publications highlighting resilience in crisis (Procurement Capacity Index and humanitarian logistics) and a generic framework for inventory procurement. Furthermore, in 2024, there will be only one publication on the integration of data mining in supplier management, marking the adoption of big data techniques for DSS.

By 2025, four articles on DSS for uncertainty trade agents, MCDM contractor selection, maturity model humanitarian logistics, and DSS for complex procurement will be available. Focus on sustainability, resilience, and the integration of AI.

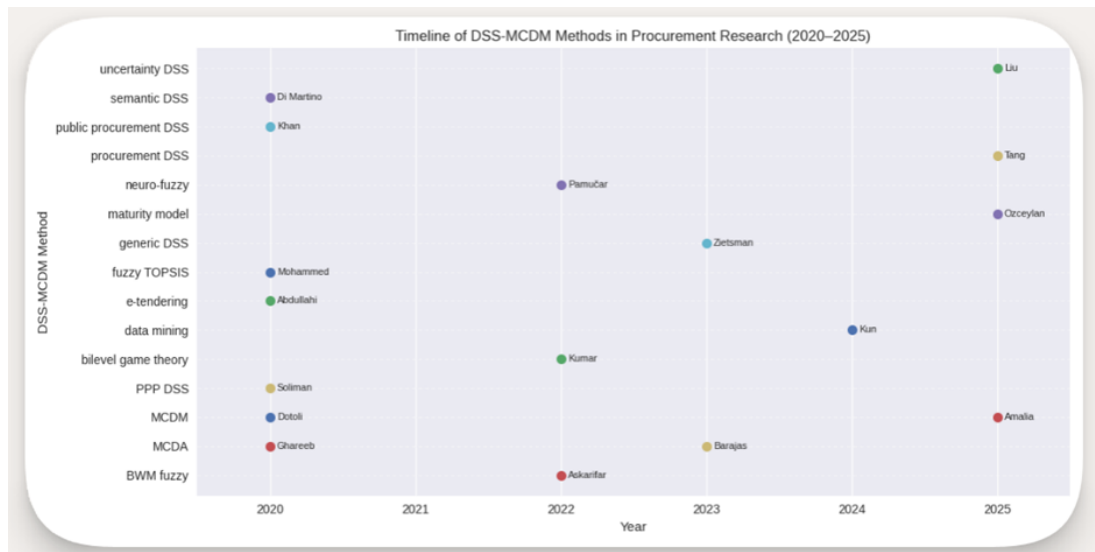


Figure 2. Article Summary

3.2.1. Application Domains

Table 1. Summary by domain

| No | Application Domains | Researcher | Key Findings |
|----|--|-----------------------------------|--|
| 1 | Trade agent procurement & sales planning | Liu, Wang, Tang [10] | DSS for procurement & sales planning under uncertainty, improving decision integration. |
| 2 | Multi-supplier price negotiation | Kumar, Gupta, Mehra [11] | Bilevel game model for competitive price targets, supporting buyers in strategic negotiations. |
| 3 | Supplier selection (case study) | Askarifar, Arabi, Alagheband [12] | Integrasi Best-Worst Method & fuzzy programming, meningkatkan akurasi pemilihan supplier. |
| 4 | Crisis procurement capacity | Barajas [13] | The Procurement Capacity Index, using MCDA, identifies the most vulnerable groups in crisis. |
| 5 | Inventory procurement planning | Zietsman, van Vuuren [14] | Generic DSS framework for central distribution, improving the efficiency of inventory procurement. |
| 6 | Sustainable supplier assessment | Mohammed [15] | Fuzzy TOPSIS & multi-objective approach, assessing suppliers based on sustainability aspects. |

| | | | |
|----|--|---|--|
| 7 | E-tendering in the public sector (Nigeria) | Abdullahi, Ibrahim, Bala [16] | E-tendering evaluation system, improving transparency & accountability of the public sector. |
| 8 | E-government services (Egypt) | Ghareeb, Darwish, Hefney [17] | MCDA for evaluating e-government services, thereby improving the quality of public services. |
| 9 | E-government business process optimization | Di Martino, Marino, Rak, Pariso [18] | Semantic DSS for validation & optimization of e-government business processes. |
| 10 | PPP procurement (Egypt) | Soliman, El-Barkouky [19] | DSS for PPP projects, supporting public-private procurement decision-making. |
| 11 | Public procurement contracting (Pakistan) | Khan, Ayyaz, Naseem [20] | DSS is integrated to optimize the public procurement contract process. |
| 12 | Public procurement tender management | Dotoli, Epicoco, Falagario [21] | MCDM for public tender management, case studies improve fairness & efficiency. |
| 13 | Supplier management (data mining) | Kun, Han, Lin, Wang, Song[22] | DSS is based on data mining algorithms for supplier management. |
| 14 | Public procurement success prediction | Pamučar, Božanić, Puška, Marinković[23] | Neuro-fuzzy system for predicting the success of companies in public procurement. |

3.2.2. The Dominant ML Method

Table 3. Summary based on dominant ML

| Researcher | ML Methods Used | Dominance / Role |
|-----------------------------------|--|--|
| Askarifar, Arabi, Alagheband [12] | Fuzzy Mathematical Programming (Best-Worst Method + fuzzy) | Dominant in supplier selection, handling the uncertainty of preferences. |
| A. Mohammed[15] | Fuzzy TOPSIS + Possibilistic Multi-Objective | Dominant for sustainable supplier assessment, integrating uncertainty & multi-objective. |

| | | |
|--|--|--|
| Pamučar, Božanić, Puška, Marinković [23] | Neuro-Fuzzy System | Dominant for sustainable supplier assessment, integrating uncertainty & multi-objective. |
| Kun, Han, Lin, Wang, Song [22] | Data Mining Algorithms | ML dominan untuk supplier management, memanfaatkan big data & pattern recognition. |
| Kumar, Gupta, Mehra [11] | Game Theory (bilevel model) | Not classic ML, but algorithmic optimization for price negotiation. |
| Di Martino, Marino, Rak, Pariso [18] | Semantic Techniques (AI-based) | Web-based semantic ML for e-government process optimization. |
| Liu, Wang, Tang [10] | Uncertainty Modeling (probabilistic DSS) | Using a probabilistic approach, not pure ML, but closer to predictive analytics. |

3.2.3. DSS's contribution to the government sector

Table 4. DSS's contribution to the government sector

| Application Domains | Researcher | Key Findings |
|---|--|--|
| Public Sector E-tendering (Nigeria) | Abdullahi, Ibrahim, Bala [16] | Develop an e-tendering evaluation system for the Nigerian public sector to enhance transparency, accountability, and efficiency in the procurement process. |
| Evaluation of e-government services (Egypt) | Ghareeb, Darwish, Hefney [17] | Using MCDA to assess the performance of e-government services, focusing on the quality of public services and the effectiveness of the digital procurement system. |
| Optimization of e-government business processes | Di Martino, Marino, Rak, Pa[21]riso [18] | DSS is based on semantic techniques for the validation and optimization of e-government business processes, strengthening digital integration in public procurement. |
| PPP procurement (Mesir) | Soliman, El-Barkouky [19] | The DSS model for Public-Private Partnership (PPP) projects supports procurement decision-making in the public sector with private collaboration. |
| Public procurement contracting (Pakistan) | Khan, Ayyaz, Naseem [20] | DSS is integrated to optimize the public procurement contract process, increasing efficiency and transparency in government procurement. |

| | | |
|--|--|---|
| Public tender (Europe, case study) | Dotoli, Epicoco, Falagario [21] | MCDM for public tender management, case studies show improved fairness, efficiency, and quality of evaluation. |
| Predicting the success of public procurement | Pamučar, Božanić, Puška, Marinković [23] | Neuro-fuzzy system to predict the company's success in participating in public tenders, supporting data-driven decision-making. |

3.3. Qualitative analysis

The DSS and MCDM procurement research for the period 2020–2025 shows a clear evolution. The year 2020 marked a significant starting point, with numerous publications emphasizing the importance of public transparency and the digitization of e-procurement, particularly in Nigeria, Egypt, Pakistan, and Europe. The dominant methods include fuzzy TOPSIS, classic MCDA, and semantic DSS, which are utilized to assess suppliers, optimize business processes, and manage public tenders.

Entering 2022, the focus shifted to strategic optimization with the emergence of game theory for price negotiation, Best-Worst Method (BWM) for supplier selection, and neuro-fuzzy systems for predicting the success of public procurement. This marks a shift from just evaluation to AI-based prediction and optimization.

In 2023, the research highlights the aspects of crisis resilience and inventory procurement efficiency. Barajas introduced the Procurement Capacity Index to identify vulnerabilities in a crisis, while Zietsman developed a generic framework for inventory procurement in distribution centres.

The year 2024 is marked by the integration of big data and data mining in supplier management, showing the adoption of more advanced analytics technology.

Finally, in 2025, it shows the diversification of themes. For example, Liu developed DSS for procurement & sales under uncertainty, Amalia emphasized MCDM for contractor selection in innovative city projects, and Ozceylan introduced a maturity assessment model for humanitarian logistics. This trend confirms the direction of research towards sustainability, resilience, and the integration of AI in DSS procurement.

The 2020 period demonstrates the dominance of research focused on the digitization of e-procurement in the public sector, with case studies spanning Nigeria, Egypt, Pakistan, and Europe. This reflects the global urgency to strengthen government procurement systems through digital technology, especially in the context of transparency and accountability.

The methodologies used in these studies are pretty diverse, but they remain concentrated on Multi-Criteria Decision Analysis (MCDA) approaches such as TOPSIS and classic MCDM, as well as integration with fuzzy/neuro-fuzzy techniques to deal with uncertainty in evaluation [24][25]. Additionally, semantic DSS is utilized to enrich the e-government business optimization process, as well as a tender evaluation system designed to enhance fairness and efficiency [26].

The primary focus of the study is clear: improving transparency, accountability, contract optimization, and the quality of public services. In other words, DSS-MCDM is positioned as a strategic tool to enhance procurement governance in the public sector, thereby reducing corrupt practices, streamlining the tender process, and increasing public trust in government institutions.

However, a significant research gap exists, as no existing article data have been found that specifically discuss e-procurement in universities. The majority of research still focuses on the context of the government and the public sector as a whole. In fact, universities, as higher education institutions,

also have complex procurement needs, ranging from laboratories and information technology to campus facilities, that demand an efficient and transparent procurement system.

4. DISCUSSIONS

Research on Decision Support Systems (DSS) in procurement has experienced rapid development since 2020. Mohamud Mohamed Hassan et al. [27] Emphasized the importance of an e-tendering evaluation system in the Nigerian public sector to improve transparency and accountability. The system is designed to reduce corrupt practices and speed up the tender process. Their findings show that digitalized procurement can significantly improve public governance. Ghareeb, et al. [17] Examined the evaluation of e-government services in Egypt using the Multi-Criteria Decision Analysis (MCDA) approach. This research highlights how DSS can be used to assess the quality of public services objectively. The MCDA enables decision-makers to consider multiple criteria simultaneously, resulting in more comprehensive evaluation results. This strengthens the role of the DSS as a strategic tool in bureaucratic reform.

Di Martino et al. [18] expand the scope by integrating semantic techniques in DSS for e-government business process optimization. This semantic approach enables the system to understand the data context more deeply. The study's results show that semantic DSS can enhance the efficiency and validation of the digital procurement process. Thus, DSS serves not only as an analysis tool, but also as an adaptive intelligent system. Soliman and El-Barkouky [32] added a Public-Private Partnership (PPP) perspective by developing a DSS model for procurement projects in Egypt. This model facilitates informed decision-making in infrastructure projects that involve public-private collaboration. Their findings confirm that DSS can strengthen transparency and accountability within PPPs. This is crucial to ensure the project's long-term sustainability.

Khan et al.[20] Highlight the Pakistani context by developing an integrated DSS for the optimization of public procurement contract processes. This research highlights the importance of systems that are adaptable to local regulations. The DSS developed is capable of increasing efficiency and transparency in government procurement. These results demonstrate the relevance of DSS in various regulatory contexts. Dotoli et al. [21] Case studies in Europe show the application of Multi-Criteria Decision Making (MCDM) in public tender management. Their findings confirm that MCDM can improve the fairness and quality of tender evaluation. By considering various criteria, DSS can help decision-makers select the most suitable provider. This strengthens public trust in the procurement system. Mohammed [28] Introduces the sustainability dimension by integrating fuzzy TOPSIS and a multi-objective approach in supplier assessment. This research is a pioneer in incorporating sustainability aspects into DSS procurement. The results show that suppliers can be judged not only in terms of cost, but also in terms of environmental and social aspects. This marks a significant shift toward sustainable procurement.

Entering 2022, the focus of research shifted towards strategic optimization. Kumar, Gupta, Mehra [24] Developed a bilevel game theory model to support buyers in price negotiations with multiple suppliers. This approach demonstrates the potential of DSS in supporting competitive strategies. The study's results show that DSS can help buyers achieve a more efficient price target. Askarifar et al.[25] Proposed the integration of the Best-Worst Method (BWM) with fuzzy programming for supplier selection. Their findings suggest that this method can improve accuracy and consistency in decision-making. With BWM, decision-makers can determine the priority of criteria more clearly. This strengthens the role of DSS in complex supplier selection.

Pamučar et al. [23] Introduced a neuro-fuzzy system to predict the success of a company in a public tender. This approach combines artificial intelligence with fuzzy logic to produce more accurate predictions. The results of the study indicate that neuro-fuzzy-based DSS can enhance companies'

chances of success in tenders. This marks a shift for DSS towards AI-based prediction. The year 2023 is marked by a focus on resilience in the face of crises. Barajas [26] developed an MCDA-based Procurement Capacity Index to identify the most vulnerable groups in crises. This research emphasizes the importance of DSS in humanitarian and crisis contexts. The results indicate that DSS can be utilized to enhance organizational capacity in disaster management.

Zietsman and van Vuuren [14] Propose a generic DSS framework for inventory procurement in distribution centres. This research emphasizes the importance of efficiency and flexibility in inventory management. The DSS developed can significantly improve inventory planning. This shows the relevance of DSS in the context of logistics and distribution. The year 2024 shows the integration of data mining algorithms in DSS for supplier management. Kun, Han, Lin, Wang, Song [22] Demonstrate how big data can be leveraged to enhance the accuracy and speed of decision-making. Data mining-based DSS enables the identification of patterns and trends in supplier data. This strengthens the role of DSS in the digital and significant data era. By 2025, research will be increasingly diverse. Liu, Wang, and Tang [10] developed a DSS for procurement planning and sales trade agents under uncertainty. This research highlights the significance of DSS in addressing uncertain market conditions. The results suggest that DSS can help trading agents make more adaptive decisions.

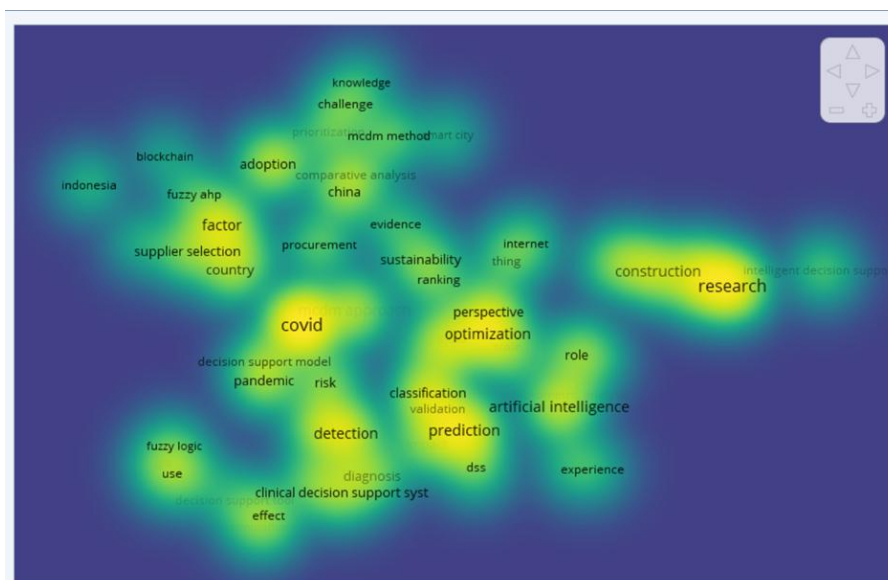


Figure 2. Vos Viewer analysis results

The results of the density visualization show that DSS-MCDM research in the context of procurement and decision-making has undergone a significant thematic shift. Keywords such as artificial intelligence, clinical decision support systems, optimization, and prediction emerged as high-density areas, indicating that AI-based approaches and predictive systems are now in the spotlight in the literature. These findings imply that DSS is no longer positioned solely as an evaluative tool, but rather has evolved into an adaptive system capable of processing large datasets and generating machine learning-based recommendations.

Research such as Areej Padmanabhan et al. [29] and Mohammed [15] Support this direction by emphasizing the importance of maturity models and fuzzy sustainability metrics in public procurement. However, the visualization also reveals a significant thematic gap. Keywords such as "Indonesia," "country," and "comparative analysis" appear in low-density zones, indicating that country-based studies, particularly in the Southeast Asian region, remain limited. In fact, the regulatory context, culture, and institutional capacity greatly affect the effectiveness of DSS in public procurement.

Therefore, cross-border research is needed that compares the implementation of DSS–MCDM in various government and higher education systems.

Based on these findings, several future research directions can be developed, including the absence of articles that specifically discuss e-procurement in universities. This highlights the need for the development of DSS tailored to academic needs, such as the procurement of laboratory equipment and IT devices. This system can integrate academic, budget, and sustainability criteria. This study is a follow-up to explore how blockchain technology can be utilized to record and verify tender processes in real-time, thereby enhancing accountability and reducing potential corruption in public procurement. Finally, it can develop Barajas Research [13]. Where DSS can be developed to measure procurement capacity in dealing with disasters or crises, including in the context of humanitarian logistics and aid distribution.

5. CONCLUSION

This study provides a comprehensive overview of the development of Decision Support Systems (DSS) and Multi-Criteria Decision Making (MCDM) in the context of procurement in the 2020–2025 period. Bibliometric analysis reveals that the initial research focuses on the issues of transparency and digitalization of e-procurement in the public sector, with classic MCDA, fuzzy TOPSIS, and semantic DSS methods as the primary approaches. Over time, research trends are shifting towards the integration of intelligent technologies, such as artificial intelligence, neuro-fuzzy systems, and data mining algorithms, which expand the role of DSS from mere evaluation to data-driven prediction and optimization.

Network visualizations, overlays, and density show that keywords such as supplier selection, optimization, and public procurement remain central themes, while new topics, including blockchain, sustainability, and clinical decision support systems, are beginning to emerge as future research directions. This confirms that DSS–MCDM is increasingly relevant in the face of global challenges, including the COVID-19 pandemic, logistics crisis, and the need for a transparent and sustainable procurement system.

The thematic discussion also revealed a significant research gap, especially in the context of higher education. Although e-procurement in the public sector has been extensively researched, no study has specifically addressed the implementation of DSS–MCDM in university procurement systems. In fact, universities have complex and strategic procurement needs, so research in this field can make a practical and academic contribution.

Thus, this study concludes that DSS–MCDM procurement has evolved from a focus on efficiency and transparency towards the integration of innovative technologies, sustainability, and resilience. The research agenda going forward needs to be directed at the development of adaptive DSS for the higher education sector, blockchain integration for transparency, as well as the application of AI in clinical and humanitarian systems. These findings are expected to contribute to the academic literature while providing practical recommendations for policymakers and institutions seeking to improve the quality of their procurement systems.

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

ACKNOWLEDGEMENT

Acknowledgement is only addressed to funders or donors and object of research. Acknowledgement can also be expressed to those who helped carry out the research.

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