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STRATEGIC SOURCING IN DATA CENTER ECOSYSTEMS: LEVERAGING AI AND COST ANALYTICS FOR COMPETITIVE ADVANTAGE

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ABSTRACT

Data center operators need to make sourcing decisions that consider energy efficiency, reliability, technical suitability, sustainability and exposure to operating costs. This study proposes an AI-based strategic sourcing model for data center uninterruptible power supply (UPS) procurement based on the publicly available data of UPS products certified by the ENERGY STAR. The framework transforms product certification data into sourcing intelligence by performing data screening, preprocessing, feature engineering, energy-loss cost analysis, multi-criteria AI-assisted scoring, product and supplier ranking, recommendation classification, clustering, explainable AI, traditional AI versus AI comparison, and robustness analysis. The final analytical sample consisted of 465 UPS models relevant to the data center from 15 suppliers. The findings indicate that a more balanced procurement decision is made with integrated AI-assisted sourcing than with single factor evaluation. Traditional efficiency-only and cost-only approaches chose CyberPower CP3000PFCRM1U, but the AI-based approach chose Eaton 5P1550IRT2UG2-L for its better overall efficiency, runtime, warranty and cost performance. The supplier robustness analysis revealed that CyberPower was the strongest supplier if suppliers with less than 10 products were not included. Explainable AI also found that energy cost per kW, efficiency, sustainability, and technical suitability were the primary factors influencing the outcomes of recommendations. The study provides a clear decision support process for converting public certification information to strategic sourcing intelligence and helps to make more balanced, sustainability-driven procurement decisions in data center ecosystems.

KEYWORDS: Strategic Sourcing, Data Center UPS, Artificial Intelligence, Cost Analytics, Supplier Selection.

1. INTRODUCTION

Cloud computing, artificial intelligence, financial services, healthcare, e-commerce, and enterprise digital operations have all become essential services for data centers. The growth of digital workloads is driving a greater need for data center operators to deliver greater energy efficiency, operational resilience, and sustainability performance. Electricity use is still a significant challenge for digital infrastructure planning (Masanet et al., 2020) and the environmental impact of data centers is not limited to electricity consumption, but also includes carbon emissions, water usage, and impacts on infrastructure (Siddik et al., 2021). As a result, infrastructure sourcing decisions are now having a greater impact on the long-term operating cost, sustainability results and competitive positioning of the infrastructure.

In data center ecosystems, uninterruptible power supply (UPS) systems play a vital role in safeguarding critical loads, ensuring power continuity during outages, and affecting energy loss cost due to conversion efficiency. While data center research typically focuses on cooling systems and computational resource optimization, UPS sourcing is also strategically significant as it has a direct impact on reliability and energy performance. The energy efficiency of data center cooling systems is a key factor in achieving operational efficiency (Huang et al., 2023), and the increasing adoption of advanced analytics for data center energy management highlights the importance of intelligent optimization (Zhao et al., 2024). These developments suggest that procurement of data center infrastructure should be viewed as a strategic sourcing problem and not a simple purchasing problem.

In the traditional UPS procurement process, the product availability, basic specifications, familiarity with the supplier, purchase price, or single-factor evaluation (such as energy efficiency) may be used. These methods may fail to consider runtime, warranty quality, technical appropriateness, sustainability features, supplier portfolio quality or operating cost based on energy loss. This presents a real-world and analytical challenge: The most energy efficient product may not be the most strategically appropriate when reliability, technical fit, cost exposure and sustainability are considered collectively. Hence, the UPS sourcing process needs a multi-dimensional decision support framework that can incorporate technical, economic and sustainability aspects.

In procurement and supply chain management, AI is increasingly being leveraged to aid supplier evaluation, automate decisions, assess risks, and provide strategic sourcing intelligence (Guida et al., 2023). AI can enhance forecasting, logistics planning, risk analysis, supplier evaluation and performance management, as revealed in broader research on the supply chain (Toorajipour et al., 2021). AI-driven innovation can also enhance the resilience and performance of supply chains in dynamic operating environments (Belhadi et al., 2024), and AI-based resilience research emphasizes the importance of analytics in decision-making in the context of uncertainty (Modgil et al., 2022). But there is not much research that has been conducted to use AI-based sourcing logic in the selection of data center UPS suppliers and products based on public product certification data.

This study concentrates on one strategic sourcing category in the data center ecosystem: UPS systems for data centers. It does not assess all types of equipment found in data centers, including servers, cooling systems, batteries, networking equipment, racks, and power distribution units. The empirical analysis is based on publicly available data on UPS products from the ENERGY STAR program and the analysis of the products is based on energy efficiency, reliability, technical suitability, sustainability, and estimated energy-loss operating cost. The cost analysis is based on operating cost due to energy losses and does not include the total cost of ownership as purchase price, maintenance cost, installation cost, battery replacement cost, downtime cost, supplier lead time and contract terms are not considered.

The study adds to the sustainable procurement and digital sourcing literature by demonstrating the potential of public certification data to be converted to decision intelligence. The research on sustainable procurement highlights the need to incorporate environmental, operational and supplier related factors in the procurement process (Kannan, 2021) and the research on Industry 4.0 indicates that advanced digital technologies can contribute to the diffusion of sustainability and to decision making in supply chains (Luthra et al., 2020). This study is novel in creating an AI-assisted strategic sourcing framework for data center UPS procurement that incorporates energy efficiency, energy-loss cost, reliability, technical suitability, sustainability, product ranking, supplier ranking, explainable AI, clustering, traditional comparison and robustness analysis.

The study has three objectives

1. To develop an AI-assisted sourcing framework for data center UPS procurement.

2. To rank UPS products and suppliers using efficiency, cost, reliability, technical suitability, and sustainability criteria.
3. To evaluate the framework through traditional comparison, explainable AI, clustering, and robustness analysis.

2. LITERATURE REVIEW

Digital transformation has transformed procurement and supply chain decision making by leveraging data, automation, analytics and platform-based coordination. Digital technologies enhance the performance of the supply chain by enhancing visibility, information processing and integration of information in the supply chain (Wamba et al., 2020). This is significant for strategic sourcing as procurement decisions are increasingly based on structured evidence and not on an informal comparison between suppliers. Decision-support systems also apply to situations of uncertainty in operations, where organisations need to deal with fluctuations in demand, disruption and risk. For instance, decision-support models created in the midst of an epidemic demonstrate the way analytics can help in the planning of supply chains in the presence of uncertainty (Govindan et al., 2020). Artificial Intelligence (AI) takes this decision-support logic further by allowing for classification, prediction, explanation and further advanced evaluation of procurement options. But, there are also challenges in implementing AI, such as data quality, organizational readiness, interpretability, and adoption (Sharma et al., 2022). Hence, when using AI in sourcing, it is important to understand that it is not a replacement for a procurement process, but rather a tool to support the decision-making process. Information sharing and agile supply chain capabilities are still vital as accurate and timely information is vital for procurement responsiveness (Alzoubi & Yanamandra, 2020). AI-powered frameworks can also revolutionize the way business data is processed into actionable intelligence for performance enhancement (Bag et al., 2021), while risk-centric logistics studies emphasize the importance of analytical tools that address uncertainty and system vulnerabilities (Choi, 2021).

Supplier selection is generally considered a multi-criteria decision making problem, as there are several criteria to consider when selecting a supplier, such as cost, quality, reliability, sustainability, technical fit, and operational risk. Integrated MMD-TOPSIS has been used for supplier selection and fair order allocation, demonstrating that ranking techniques can help in the transparent evaluation of multiple criteria (Aouadni & Euchi, 2022). The research on green supplier selection based on fuzzy AHP also shows that the environmental and operational criteria can be formally included in the sourcing process, and not only as a secondary criterion (Ecer, 2022). Similarly, fuzzy consistency and prioritization methods show the value of structured weighting for complex managerial decisions (Pamucar et al., 2020). The studies back the procurement of multi-criteria scoring and ranking, but the majority of them are not directly related to data center UPS procurement. When choosing a data center ecosystem, it is important to consider the performance of the supplier and the product, as well as the energy efficiency, infrastructure reliability and sustainability impact. This is a good environment for a strategic sourcing initiative, decision analytics, and cost-based evaluation to be combined in UPS procurement.

Sustainability and energy efficiency are key issues in data center ecosystems, as the decisions made about infrastructure can have a direct impact on the cost, resilience, and sustainability of the data center. Research on waste heat utilization in data centers demonstrates that waste heat recovery can enhance the sustainability of data center operations (Pan et al., 2021). The critical success factors for sustainable data center development, highlighted in the research on green energy integration, emphasize the importance of considering infrastructure not just technically, but also from an environmental standpoint (Chountalas et al., 2025). Energy-efficient resource provisioning studies also reveal that computational and infrastructure decisions can help in reducing the energy consumption in cloud data centers (Dixit & Kumar, 2025). Recent studies on sustainable and transient data center design also show a trend towards multi-objective optimization in future computing systems (Li et al., 2026). Previous basic research is still valid as it has shown the significance of coordinated energy-management, renewable integration and operational optimization strategies in data centers (Oró et al., 2015; Khalaj et al., 2015). Overall, the literature reveals that the progress in AI-enabled supply chains, MCDM-based supplier selection, sustainable procurement and data center energy optimization is good. But, current research focuses on AI procurement, supplier selection and data centre energy optimization mostly as isolated processes. Few studies have incorporated these aspects into an AI-based strategic sourcing solution for data center UPS procurement, based on public certification information. This gap is addressed by the present study, which integrates the data from ENERGY STAR UPS, energy-loss cost analytics, supplier/product ranking, explainable AI, clustering, and robustness analysis to help achieve competitive advantage in data center UPS procurement.

3. METHODOLOGY

3.1. Research Design

The research design used in this study was quantitative and data-driven, which aimed to create an AI-based strategic sourcing model for data center uninterruptible power supply (UPS) procurement. The research was designed as an applied decision-analytics study, in which public product certification data were converted to sourcing intelligence for supplier and product evaluation. The chosen sourcing category was data center UPS systems and the scope was restricted to UPS supplier and product selection as one strategic sourcing problem in the overall data center ecosystem. The research was conducted in a sequential analytical process starting with the collection of the datasets, followed by the filtering of the data centers, the selection of variables, the data pre-processing, the cost analytics, the AI-assisted scoring, the ranking of products and suppliers, the classification of the recommendations, the clustering, the explainable AI, the traditional comparison, and the robustness analysis as illustrated in Figure 1.

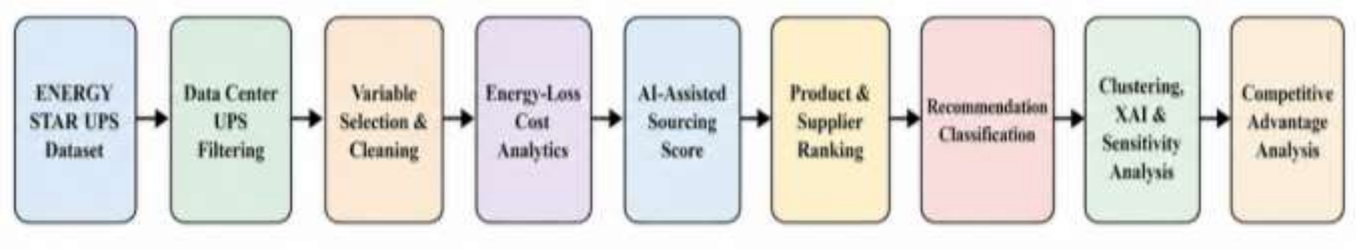

Figure 1: Methodological Workflow from Product Certification Data to Strategic Sourcing Intelligence.

3.2. Dataset Collection

The empirical data were gathered from the publicly available ENERGY STAR Certified Uninterruptible Power Supplies dataset from the ENERGY STAR Data Portal (ENERGY STAR, 2026).

This dataset was chosen due to the availability of structured, transparent and reproducible product level information on certified UPS models. It contains supplier information, brand, model details, application type, output capacity, energy efficiency, runtime, warranty, energy storage attributes, network capability, certification information, market coverage and sustainability information. These variables are appropriate for creating a strategic sourcing framework because they enable UPS products to be assessed in terms of technical, economic, reliability, and sustainability.

3.3. Dataset Scope and Sampling

The study focused only on UPS products relevant to data center applications. ENERGY STAR UPS products are available for a variety of markets, including consumer, commercial and data center applications. Hence, a purposive and criteria-based sampling was employed to keep UPS models related to data center applications. The unit of analysis for this unit was the UPS product model. Supplier-level evaluation was carried out by combining product-level sourcing indicators. The dual level enabled the study to analyse the suitability of individual UPS products as well as the performance of UPS supplier portfolios.

3.4. Variable Selection

Variables were chosen based on their relevance to the strategic sourcing decisions. The chosen variables were categorized into supplier identity, product identity, capacity, energy efficiency, reliability, technical suitability, digital integration, sustainability, and certification-related dimensions. Manufacturers, brands, models, and product records were identified using supplier and product variables. Power and energy-performance analysis was assisted by capacity and efficiency variables. The time to run and warranty were used as measures of reliability. Technical suitability was represented by the suitability of the rack, the availability of outlets, network connections and communication related variables. Sustainability-related indicators were used such as take-back programs, battery recycling information, energy storage technology and certification attributes.

The logic for the variables selected assumed that UPS sourcing is multi-dimensional. High efficiency products are not always the optimal strategic sourcing choice when they have low runtime, warranty coverage, technical compatibility or sustainability. Selected attributes were therefore normalized into sourcing indicators to facilitate the comparison of the UPS models.

3.5. Data Pre-processing

Data preprocessing was carried out to make the data consistent prior to analytical modeling. The preprocessing steps involved in the process were column standardization, duplicate treatment, data-type conversion, handling missing values, categorical standardization, and preparing variables for feature engineering. Efficiency, output power, runtime, warranty and cost-related variables were transformed into quantitative data. The categorical variables (rack mountability, communication support, network capability, energy storage technology and sustainability attributes) were standardized to minimize inconsistencies in product records.

Variables with missing values were treated appropriately to the analysis of each variable. Where possible, numeric variables were retained that could be converted or imputed suitably, and categorical variables were converted to consistent sourcing indicators. When information was missing, it was interpreted with caution to prevent unsupported advantages being attributed. The goal of the preprocessing was to develop a clear and repeatable sourcing data set, not to artificially boost product rankings.

3.6. Cost Analytics

Operating cost logic based on energy loss was used to develop cost analytics. Energy loss during operation was estimated using UPS efficiency. The estimated energy loss was then converted to annual energy-loss exposure based on continuous operating assumptions, and electricity-price assumptions were applied to estimate annual energy-loss cost. This cost component was included in the operational cost indicator in the sourcing framework.

The cost model was deliberately restricted to operating cost based on energy loss. It was not considered as full TCO since the public dataset does not contain the purchase price, installation cost, maintenance cost, service contract cost, downtime cost, battery replacement cost, disposal cost, supplier lead time, or negotiated contract terms. Hence, the cost analytics component should be seen as an efficiency adjusted operating cost estimate rather than a full lifecycle cost model.

3.7. AI-Assisted Sourcing Score

The AI-assisted sourcing score is a multi-criteria decision support measure. It combined five key sourcing factors: energy efficiency, reliability, technical suitability, sustainability, and energy loss cost. All dimensions were standardized to allow comparison of products. These dimensions were combined in a weighted fashion to arrive at the final score which was used to rank UPS products.

Product-level scores were also consolidated at the supplier level to measure the supplier sourcing performance. Product ranking was used to determine the best individual UPS models and supplier ranking was used to determine the average performance of the supplier portfolio. The quartile-based classification rule was used to generate the categories of Recommendation: The top quartile of AI sourcing scores was classified as Recommended, the middle quartile was classified as Conditionally Recommended, and the lowest quartile was classified as Not Recommended. This classification enabled managerial interpretation by converting continuous sourcing scores into actual procurement categories.

3.8. Evaluation and Robustness Metrics

The framework was tested through product ranking, supplier ranking, recommendation classification, clustering, explainable AI, traditional comparison and robustness checks. To check whether the model was able to consistently reproduce the recommendation logic generated by the sourcing framework, the accuracy, precision, recall, F1-score, confusion matrix and cross validation were used to assess the recommendation classification.

To segment UPS products into strategic sourcing groups, the features relevant to sourcing were used and the K-Means clustering technique was applied. The silhouette analysis was used to evaluate the cluster quality. Random Forest feature-importance analysis was used to apply Explainable AI to determine which variables were most important in the classification of recommendations. The explainable AI part was understood to be a way to grasp the internal sourcing logic, rather than a prediction of actual sourcing actions.

Robustness analysis was conducted to determine if the product rankings were consistent across alternative assumptions. Electricity-price scenarios and alternative sourcing-weight strategies were analyzed using sensitivity analysis. Further validation was conducted by applying TOPSIS benchmarking, stochastic weight perturbation and supplier product-count filtering. These checks examined the sensitivity of the rankings to managerial priorities, cost assumptions, methodology, and supplier portfolio size.

3.9. Ethical Considerations

The study did not include human subjects, personal data, confidential procurement records, or private supplier contracts. Thus, the ethical risk was minimal. The analysis was carried out in a transparent and reproducible manner. Supplier and product rankings were not seen as an absolute measure of supplier quality or market performance, but rather as decision support outputs. The study also refrained from overclaiming by focusing on the concept of competitive advantage as better sourcing decision quality, not as direct evidence of firm-level financial performance, realized procurement savings or operational uptime improvement.

4. RESULTS

4.1. Dataset Screening and Analytical Sample

The analysis started with the ENERGY STAR certified UPS dataset and was focused on products relevant to data center UPS sourcing. There were 921 UPS records and 102 variables in the original dataset. 471 records were kept for data center relevance after screening. After duplicate removal, data cleaning and analytical preparation, the final sample consisted of 465 UPS models from 15 suppliers as mention in Table 1. This last dataset was used to perform cost analytics, develop AI-based sourcing scores, rank suppliers and products, classify recommendations, cluster, explainable AI, traditional comparison and robustness analysis.

Table 1: Dataset Screening and Analytical Sample.

Item	Value
Raw UPS records	921
Raw variables	102
Data center-relevant records	471
Cleaned analytical records	465
Final suppliers	15
Final product-ranking unit	UPS model

4.2. Energy-Loss Cost Analytics

The energy-loss cost analysis calculated the annual operating-cost exposure due to UPS energy conversion losses. The output power, UPS efficiency, annual operating hours and electricity-price assumptions were used in the calculation. The results are to be interpreted as energy loss based operating cost and not as full total cost of ownership as purchase price, installation, maintenance, service contracts, battery replacement, downtime and supplier contract terms were not available in the public data set.

Table 2: Electricity-Price Cost Scenario Summary.

Scenario	Electricity price ($/kWh)	Total annual energy cost ($)	Average annual cost per kW ($)
Low energy price	0.08	436,775	32.39
Base energy price	0.12	655,162	48.59
High energy price	0.20	1,091,937	80.98

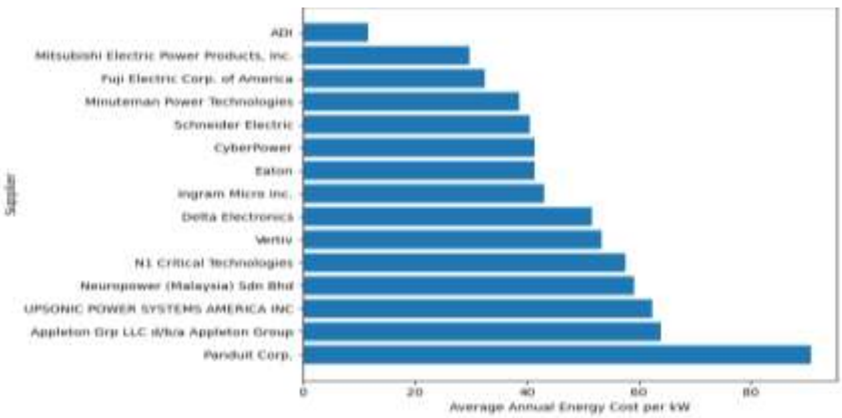

Figure 2: Estimated Annual Energy Cost by Supplier.

The findings show that electricity-price assumptions substantially affect estimated annual energy-loss cost. Under the base price of $0.12/kWh, the total estimated annual energy-loss cost was approximately $655,162 as described in Table 2. Under the high-price scenario, it increased to approximately $1.09 million as shown in Figure 2. This confirms that efficiency differences have direct sourcing relevance because inefficient UPS systems can increase long-term operating-cost exposure.

This figure compares supplier-level average annual energy-loss cost per kW. It supports the cost analytics component of the study by showing differences in operating-cost exposure across suppliers.

4.3. AI-Based Product Ranking

The AI-assisted sourcing score ranked UPS products by integrating energy efficiency, reliability, technical suitability, sustainability, and energy-loss cost. The highest-ranked product was Eaton 5P1550IRT2UG2-L, with an AI sourcing score of 0.7213 in Table 3. The leading products were not selected only because of maximum efficiency or minimum energy cost; instead, they reflected stronger overall sourcing balance across efficiency, runtime, warranty, cost, and technical suitability.

Table 3: Top AI-Ranked UPS Products.

Rank	Supplier	Model	Efficiency (%)	Runtime 100% load (min)	Warranty (yrs)	Energy cost/kW ($)	AI score
1	Eaton	5P1550IRT2UG2-L	98.9	6	8	11.692	0.7213
2	Eaton	5P1550RT2UG2-L	98.7	6	8	13.846	0.7113
3	Eaton	5P1000RT2UG2-L	98.6	9	8	14.926	0.7108
4	CyberPower	CP3000PFCRM1U	99.4	1	3	6.345	0.7106
5	CyberPower	CP2000PFCRM1U	99.3	3	3	7.410	0.7093

The top product-level sourcing jobs went to Eaton and CyberPower. The efficiency and energy-loss cost of CyberPower products were very high and low, respectively, and the overall performance of Eaton products was higher due to their higher efficiency and better runtime and warranty. This illustrates the importance of the integrated sourcing evaluation instead of the single-criterion procurement logic.

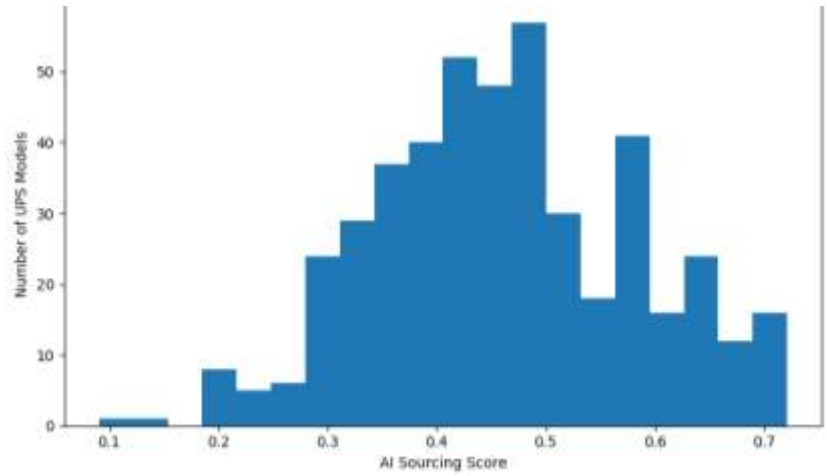

Figure 3: AI Sourcing Score Distribution.

This Figure 3 shows how UPS products are distributed across the AI sourcing score range.

4.4. Supplier-Level Ranking and Robustness

The supplier-level ranking was determined by the sum of the product-level AI sourcing scores. In the overall ranking, ADI was the top performer with an average AI score of 0.7060. This result must be taken with a pinch of salt, however, as there were only two products in the cleaned dataset. A supplier robustness check was, therefore, carried out with a minimum threshold of 10 products. In this more conservative scenario, CyberPower was first, followed by Minuteman Power Technologies and Eaton as shown in Table 4.

Table 4: Supplier Ranking and Supplier-Robustness Check.

Panel	Rank	Supplier	Products	Average AI score	Additional indicator
Full ranking	1	ADI	2	0.7060	100.00% recommended
Full ranking	2	CyberPower	33	0.5379	51.52% recommended
Full ranking	3	Minuteman Power Technologies	23	0.5095	60.87% recommended
Full ranking	4	Eaton	89	0.5027	52.81% recommended
Full ranking	5	Schneider Electric	39	0.4949	0.00% recommended
Robust ranking	1	CyberPower	33	0.5379	6.345 min cost/kW
Robust ranking	2	Minuteman Power Technologies	23	0.5095	13.846 min cost/kW
Robust ranking	3	Eaton	89	0.5027	11.692 min cost/kW
Robust ranking	4	Schneider Electric	39	0.4949	32.511 min cost/kW
Robust ranking	5	Delta Electronics	13	0.4313	9.547 min cost/kW

The robustness check eliminates suppliers with fewer than 10 products from the suppliers' portfolio, which helps to limit supplier portfolio-size bias. This alters the supplier-level interpretation: ADI is still a strong small portfolio supplier, while CyberPower is the most robust supplier-level sourcing option with its high level of product representation, high average AI score and low energy-loss cost exposure.

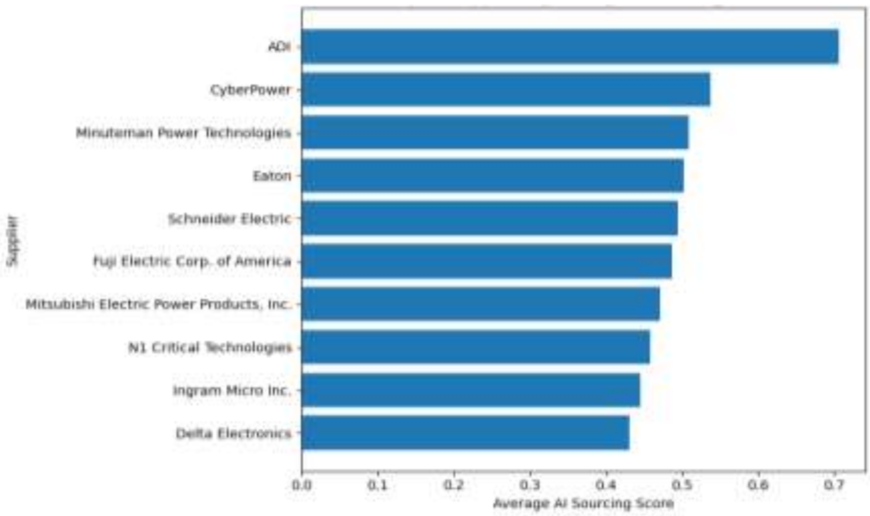

Figure 4: Top 10 Suppliers by Average AI Sourcing Score.

This Figure 4 presents the supplier-level average AI sourcing score. It visually supports the full supplier ranking and highlights differences in supplier-level sourcing performance.

4.5. Recommendation Classification and Explainable AI

A quartile-based rule was used to classify UPS products into sourcing categories. The top 25 percent was considered Recommended, the middle 50 percent Conditionally Recommended and the lowest 25 percent Not Recommended. This resulted in well-balanced categories for managerial interpretation and explainable AI analysis as mentioned in Table 5.

Table 5: Recommendation Classification and Explainable AI Summary.

Panel	Metric / Feature	Value
Classification	Recommended	117 models; 25.16%
Classification	Conditionally Recommended	232 models; 49.89%
Classification	Not Recommended	116 models; 24.95%
Model performance	Accuracy	0.9231
Model performance	Weighted F1-score	0.9227
Model performance	Macro F1-score	0.9231
Feature importance	Energy cost per kW	0.3207
Feature importance	Efficiency	0.3067
Feature importance	Sustainability	0.1897
Feature importance	Technical suitability	0.0799

The classification results indicate that approximately 25% of the UPS models were classified as Recommended, and almost half were conditionally suitable based on sourcing priorities or technical requirements. The Random Forest explainability model had high classification accuracy and it was found that energy cost per kW and efficiency were the most significant factors in determining the recommendation results. Sustainability and technical suitability also played a role, and this was found to be the case, as the sourcing framework was not solely cost or efficiency driven.

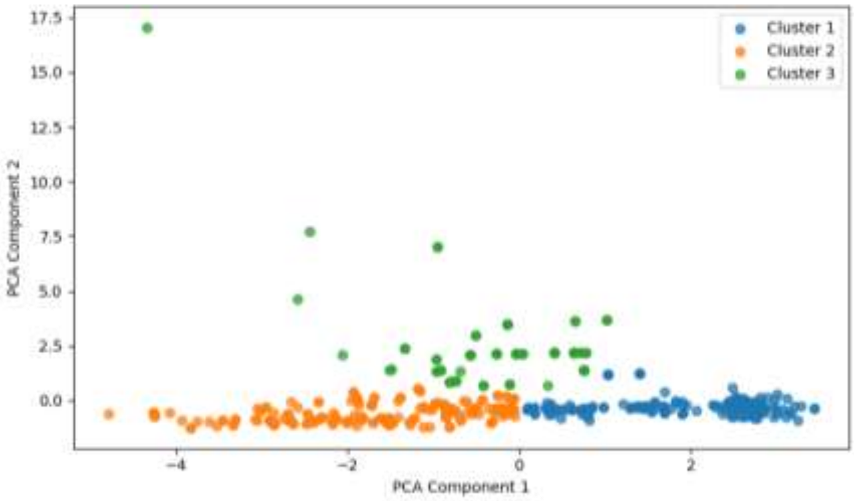

Figure 5: K-Means Cluster Visualization Using PCA.

This Figure 5 visualizes the UPS product clusters using two principal components. It supports the segmentation analysis by showing how UPS products group according to sourcing-relevant performance characteristics.

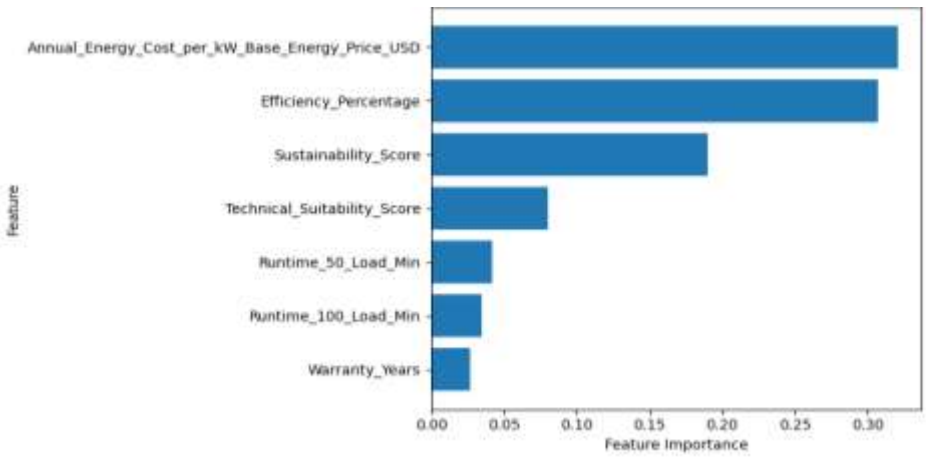

Figure 6: Random Forest Feature Importance.

This Figure 6 shows the relative importance of the main variables used in the recommendation classification model. It supports the explainable AI component by identifying the strongest drivers of UPS sourcing recommendations.

4.8. Traditional Comparison, Robustness, and Sensitivity

The traditional comparison was based on the question of whether the single factor sourcing methods were able to identify the same UPS model as the integrated AI framework. Both the efficiency-only and cost-only approaches selected CyberPower CP3000PFCRM1U, which had 99.4% efficiency and the lowest energy cost per kW at $6.345. The AI-integrated model, on the other hand, chose Eaton 5P1550IRT2UG2-L, which was slightly less efficient with a rating of 98.9%, but offered better run time and warranty performance with an energy cost per kW of

$11.692 as discussed in Table 6. This finding indicates that single factor sourcing may not consider the bigger picture of procurement value, and AI-powered sourcing can help strike a balance between cost, efficiency, reliability, and technical suitability.

Table 6: Robustness and Sensitivity Summary.

Robustness check	Test basis	Key result
Electricity-price sensitivity	Low, base, and high electricity prices	Top-10 overlap = 100%; Spearman = 1.000
Weight strategy sensitivity	Cost-, reliability-, and sustainability-focused weights	Top-10 overlap = 80%, 80%, and 50%
TOPSIS benchmark	AI ranking compared with TOPSIS ranking	Spearman = 0.6497; top-10 overlap = 30%
Stochastic weight robustness	1,000 randomized weight simulations	Mean top-10 overlap = 84.98%; mean Spearman = 0.9907
Most stable top product	Weight perturbation outcome	Eaton 5P1550IRT2UG2-L selected in 67.3% of runs

The robustness analysis reveals that the top-10 ranking under the balanced model remained unchanged after electricity-price changes as the energy-loss costs were scaled proportionately. The impact was greater on weight changes, particularly under sustainability assumptions, with top-10 overlap dropping to 50%. The TOPSIS benchmark showed moderate agreement with the AI ranking, showing that there are different sourcing trade-offs between the various multi-criteria methods. Stochastic weight robustness, however, showed good overall ranking stability with a mean top-10 overlap of 84.98% and a mean Spearman correlation of 0.9907.

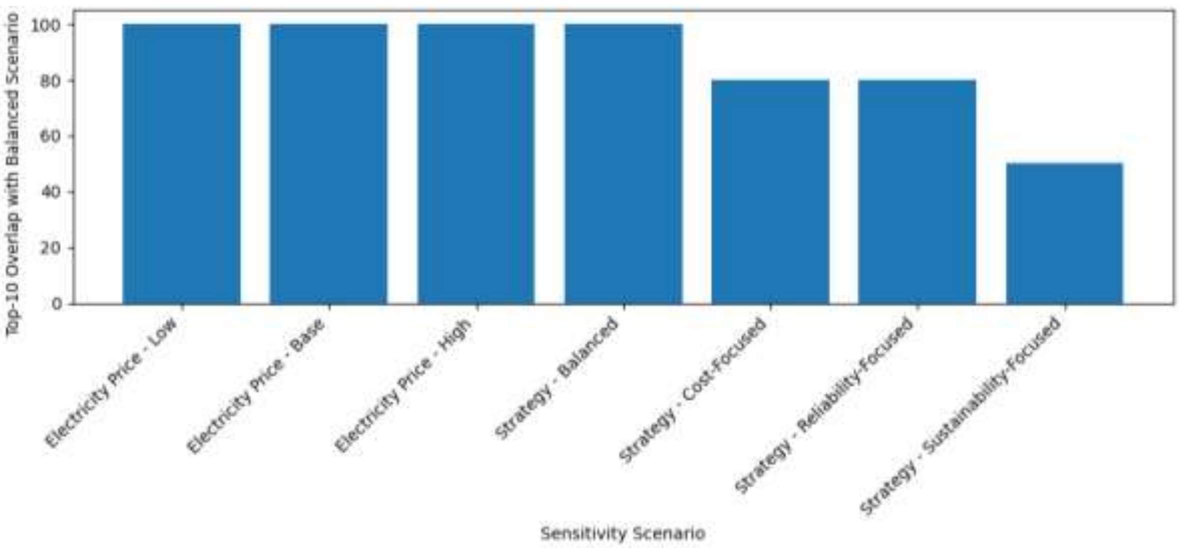

Figure 7: Sensitivity Analysis: Top 10 Ranking Overlap.

This Figure 7 shows how the top-10 product ranking changes under alternative electricity-price and sourcing-weight scenarios. It supports the robustness analysis by showing that rankings are stable under price changes but more sensitive to managerial weighting priorities.

5. DISCUSSION

The results show that strategic sourcing with the aid of AI can enhance the data center UPS procurement process by combining efficiency, energy-loss cost, reliability, technical suitability, sustainability, and supplier-level performance in one decision-support process. The main finding is that the best UPS in terms of efficiency or cost does not necessarily represent the best strategic sourcing option. The traditional efficiency-only and cost-only methods chose CyberPower CP3000PFCRM1U, while the integrated AI-based process picked Eaton 5P1550IRT2UG2-L for its high efficiency, runtime and warranty capabilities. This means that single-criterion procurement may fail to consider the value of the sourcing, especially when reliability and technical continuity are key factors in the data center's operation. The results of the suppliers also show the need for robustness analysis. While ADI was the top supplier in the overall supplier ranking, the caution was needed due to the small product portfolio. If a minimum product-count threshold was used, CyberPower proved to be the best supplier-level option, indicating that supplier evaluation should consider both average performance and portfolio depth. The clustering results also reveal that the UPS products can be divided into high priority, high cost/lower efficiency, and specialized long runtime groups, which can help the sourcing managers to match the product selection with the various operating priorities.

This is in line with previous studies on AI-driven procurement and supply chain analytics. According to Guida et al. (2023) and Toorajipour et al. (2021), AI can enhance procurement and supply chain decision-making by analyzing intricate data and assisting in the assessment of suppliers. This study takes that argument one step further and uses AI-assisted scoring, explainable AI, clustering and robustness analysis on public product certification data to apply it to the sourcing of UPSs in data centers. The findings also align with sustainable procurement research that states that environmental, operational and supplier related factors should be taken into account while making procurement decisions (Kannan, 2021; Luthra et al., 2020). Furthermore, the focus on energy-loss cost is consistent with the energy literature in data centers that energy efficiency and infrastructure decisions continue to be key factors in data center sustainability and cost management (Masanet et al., 2020; Siddik et al., 2021).

The study has implications for procurement managers, data center operators and infrastructure planners. It offers an open way to transform public certification information into actionable sourcing intelligence. The framework can be used to help shortlist products, benchmark suppliers, compare energy costs, source riskily and for sustainability. It also enables managers to avoid relying on a single measure of performance by allowing them to make trade-offs between cost, efficiency, reliability, and technical suitability.

But the study has its drawbacks. It only considers UPS systems, and does not consider other categories of data center infrastructure. The cost model is based on the estimation of the operating cost based on the loss of energy and not on the total cost of ownership. Purchase price, maintenance cost, supplier lead time, service quality, downtime risk, battery replacement cost and contract terms are not included in the dataset. Further research could incorporate actual procurement data, expert weighting, lifecycle cost information, supplier performance metrics, and other infrastructure types. In addition, the proposed framework would benefit from further validation with industry case studies or expert decision panels to further validate the practical generalizability of the framework.

6. CONCLUSION

This study proposed an AI-based strategic sourcing framework for data center UPS procurement, which combined the data of ENERGY STAR certified UPS products, energy-loss cost analysis, reliability indicators, technical suitability, sustainability attributes, product and supplier ranking, explainable AI, clustering and robustness analysis. The framework addresses the need for greater transparency and multi-dimensional sourcing decisions in data center ecosystems where UPS systems have an impact on operational continuity, energy efficiency and long-term cost exposure. The results indicate that using AI for sourcing offers a more well-rounded procurement decision compared to traditional one-dimensional sourcing. The two models selected by efficiency-only and cost-only methods were both CyberPower, but the integrated AI-based approach chose an Eaton model due to its high efficiency and superior runtime and warranty performance. This means that the most efficient product or product with the lowest energy loss cost is not always the best strategic sourcing product, but the product that best balances all of the procurement-relevant criteria. The supplier-level analysis also illustrated the benefits of robustness checks. ADI was the top supplier in the overall supplier ranking, but the limited number of products meant that this result was taken with a pinch of salt. If a minimum product count was used, CyberPower proved to be the most robust supplier level solution. The clustering and explainable AI results also reinforced the framework by pinpointing strategic product segments, and by demonstrating that energy cost per kW, efficiency, sustainability, and technical suitability were important factors in the outcomes of the recommendations. The study adds to the strategic sourcing, data center procurement, and AI-driven decision analytics by demonstrating the potential of public certification data to be converted into actionable sourcing intelligence. In practice, the framework can be used for UPS product shortlisting, supplier benchmarking, cost-efficiency evaluation and procurement for sustainability. The study does have limitations, however, due to the fact that it only covers UPS and the lack of purchase price, maintenance cost, supplier lead time, downtime risk, service quality and contract data. The framework should be expanded in the future, based on lifecycle cost data, expert-based weighting, real procurement records, supplier performance indicators, and other data center infrastructure categories.

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