MACHINE LEARNING AND MCDM MODEL FOR LOCAL FOOD SUPPLIER SELECTION IN "MAKAN BERGIZI GRATIS"

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Abstract— *The procurement of local food for Indonesia's Makan Bergizi Gratis program requires recurring supplier decisions across price, quality, delivery, capacity, and governance criteria. This study presents a reproducible, governance-aware proof-of-concept architecture that integrates supervised machine learning, the Analytic Hierarchy Process (AHP), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The experiment used 240 synthetic supplier-month observations representing 24 suppliers across ten procurement cycles and eight operational criteria. Logistic regression, support vector machine, gradient boosting, and random forest were evaluated using a stratified 70:30 holdout split and five-fold cross-validation. Random forest importance was combined equally with AHP weights before TOPSIS ranking. Logistic regression achieved the strongest holdout performance (accuracy 0.792; F1 score 0.795; AUC 0.899). Delivery reliability received the largest hybrid weight (0.201)followed by quality conformity (0.163) and continuity (0.149). Supplier S01 ranked first with a closeness coefficient of 0.812. Sensitivity tests produced Spearman correlation of 0.946–0.977 across alternative weighting scenarios. The contribution is a transparent separation of predictive evidence, normative priorities, mandatory compliance screening, and reviewable ranking for the MBG context. Because both observations and eligibility labels are synthetic, the results demonstrate computational feasibility only and are not procurement recommendations.*

Keywords: *Food Supply Chain, Machine Learning, MBG, MCDM, Supplier Selection.*

Intisari— Pengadaan pangan lokal untuk program Makan Bergizi Gratis di Indonesia memerlukan pengambilan keputusan pemasok secara berulang dengan mempertimbangkan kriteria harga, kualitas, pengiriman, kapasitas, dan tata kelola. Penelitian ini menyajikan arsitektur pembuktian konsep (proof-of-concept) yang dapat direproduksi dan memperhatikan aspek tata kelola, yang mengintegrasikan supervised machine learning, Analytic Hierarchy Process (AHP), dan Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Eksperimen menggunakan 240 observasi sintetis pemasok per periode yang merepresentasikan 24 pemasok dalam sepuluh siklus pengadaan dan delapan kriteria operasional. Logistic regression, support vector machine, gradient boosting, dan random forest dievaluasi menggunakan pembagian data holdout terstratifikasi 70:30 dan cross-validation lima lipatan. Tingkat kepentingan fitur dari random forest digabungkan secara seimbang dengan bobot AHP sebelum dilakukan pemeringkatan menggunakan TOPSIS. Logistic regression menghasilkan kinerja holdout terbaik dengan akurasi 0,792, skor F1 sebesar 0,795, dan AUC sebesar 0,899. Keandalan pengiriman memperoleh bobot hibrida terbesar sebesar 0,201, diikuti oleh kesesuaian kualitas sebesar 0,163 dan kontinuitas sebesar 0,149. Pemasok S01 menempati peringkat pertama dengan koefisien kedekatan sebesar 0,812. Pengujian sensitivitas menghasilkan korelasi Spearman sebesar 0,946–0,977 pada berbagai skenario pembobotan. Kontribusi penelitian ini adalah pemisahan yang transparan antara bukti prediktif, prioritas normatif, penyaringan kepatuhan wajib, dan pemeringkatan yang dapat ditinjau dalam konteks MBG. Karena observasi dan label kelayakan yang digunakan merupakan data sintetis, hasil penelitian hanya menunjukkan

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kelayakan komputasional dan tidak dimaksudkan sebagai rekomendasi pengadaan.

Kata Kunci: *Rantai Pasok Pangan, Pembelajaran Mesin, MBG (Makan Bergizi Gratis), Pengambilan Keputusan Multi-Kriteria (MCDM), Pemilihan Pemasok.*

INTRODUCTION

The Makan Bergizi Gratis program places food procurement at the centre of a public service whose reliability depends not only on menu design but also on the capacity of local supply networks to provide safe and timely inputs. The technical governance framework published by the National Nutrition Agency establishes operational guidance for the program and is accompanied by food safety and distribution documents for service units (Badan Gizi Nasional, 2025). In this setting, supplier selection is not a routine administrative comparison of quotations. It is a decision under multiple, partially competing objectives. A low price can be attractive for budget control, yet it may become operationally costly when it is accompanied by inconsistent volume, delayed deliveries, weak traceability, or nonconforming food quality. Such trade offs are particularly consequential for perishable commodities because a failure at the supplier level can affect meal preparation, schedule adherence, and the safety assurance of subsequent handling.

Recent studies in agro industrial and food related supply chains similarly position supplier selection as a complex evaluation problem. Dania et al. (2023) identify quality, delivery, price, and service related factors as recurrent dimensions of supplier performance in agro industrial supply chains. Handayani et al. (2025) show that AHP, TOPSIS, and fuzzy approaches remain prominent in decisions involving perishable products because these methods make heterogeneous criteria comparable. The relevance of these dimensions should not obscure their contextual character. Food procurement for MBG is locally embedded, operationally frequent, and closely coupled with food safety requirements. A useful model must therefore retain visible criteria and a traceable ranking logic while responding to patterns in supplier performance data.

Multi criteria decision making offers a systematic basis for negotiating such trade offs. AHP supports the derivation of interpretable preference weights and provides a consistency check for pairwise judgments, whereas TOPSIS ranks alternatives according to their distance from an ideal and an anti ideal solution (Basílio et al., 2022; Salomon & Gomes, 2024; Xie et al., 2022). However, conventional MCDM remains dependent on ex ante weights. Related applications also demonstrate the methodological diversity of fuzzy and hybrid MCDM approaches, but method diversity does not itself resolve the problem of data responsive weighting (Chen et al., 2023; Khulud et al., 2023). Even where the weights are logically defensible, they can underrepresent changing evidence in delivery records, quality inspection results, or capacity fluctuations. A static weighting scheme can thus appear transparent while remaining insufficiently responsive to observable performance variation.

Machine learning can complement MCDM by identifying patterns associated with supplier eligibility or operating outcomes. Studies by Ali et al. (2023), Abdulla et al. (2023), Abdulla and Baryannis (2024), and Islam et al. (2021) demonstrate that classification and interpretable feature importance can reduce the burden of evaluating numerous supplier attributes. Yet the use of machine learning alone raises a different concern. A predicted eligibility score can be informative, but it does not automatically provide a procurement ranking that stakeholders can interrogate criterion by criterion. The practical challenge is consequently not to replace decision makers with a classifier, but to combine data driven evidence with a ranking procedure that remains auditable.

This study addresses that challenge through a governance-aware hybrid architecture connecting supervised machine learning, AHP, and TOPSIS. The methodological components are established; novelty is therefore not claimed at the algorithmic level. Instead, the study contributes an MBG-specific decision protocol that (1) separates noncompensatory food-safety screening from compensatory ranking, (2) reconciles data-derived importance with explicit normative priorities through a reproducible weighting equation, and (3) reports ranking sensitivity so that close alternatives remain subject to documented human review. The computational experiment is explicitly bounded as a proof of concept rather than evidence about observed MBG suppliers. The research asks which classifier performs best in the constructed task, which criteria dominate the hybrid weights, and how stable the ranking is under alternative priorities. This bounded architecture is intended for subsequent validation with verified local procurement records and stakeholder-elicited judgments.

MATERIALS AND METHODS

This study used a quantitative computational design to test the feasibility of a hybrid supplier selection model. The design has a pragmatic epistemic orientation: supplier performance is

represented through measurable operational indicators, while the final choice is recognised as a value laden ranking decision. Consequently, prediction and preference aggregation were treated as complementary rather than interchangeable stages. No human participant records, proprietary procurement records, or personal data were used. The data were generated synthetically with a fixed random seed, so the analysis is fully reproducible in structure but must not be read as an estimate of actual supplier behaviour in any MBG location.

The simulated dataset comprised 240 supplier-month observations: 24 suppliers across ten procurement cycles. Supplier-level baselines were drawn from constrained distributions, after which cycle-level variation represented changes in price, delivery, capacity, continuity, and traceability. The eligibility label was generated from a latent operational-performance function plus an explicit food-safety requirement, yielding 122 eligible and 118 noneligible observations. Because both predictors and labels follow researcher-defined rules, high classification scores and resulting supplier ranks may partly reproduce the simulation structure. These outputs are used only for pipeline verification and illustration; they cannot validate causal claims, predict a real supplier's future performance, or substitute for historical procurement records.

Table 1 operationalises the criteria used in the model. The dimensions were selected because supplier selection research in food and agro industrial settings repeatedly identifies price, quality, delivery, capacity, continuity, and compliance as decision relevant characteristics (Ada, 2022; Dania et al., 2023; Handayani et al., 2025). Safety compliance was used as a binary criterion to reflect a minimum governance requirement, while the remaining variables retained continuous values. Price and distance were cost criteria. The other variables were benefit criteria.

Table 1. Decision Criteria and Operationalisation

Code	Criterion	Observed Range	Type	Operational Definition
C1	Price index	82.00 to 111.86	Cost	Relative price per supply cycle
C2	Quality conformity	76.72 to 100.00	Benefit	Inspection conformity percentage
C3	Delivery reliability	63.53 to 100.00	Benefit	On time and complete delivery percentage
C4	Capacity adequacy	53.37 to 100.00	Benefit	Ability to meet requested volume
C5	Continuity score	66.49 to 100.00	Benefit	Consistency across procurement cycles
C6	Distance	3.00 to 90.41 km	Cost	Transport distance to service unit
C7	Food safety compliance	0 or 1	Benefit	Minimum food safety requirement
C8	Traceability score	30.00 to 100.00	Benefit	Completeness of product origin records

Source: (Research Results, 2026)

The data were partitioned into 70 percent training data and 30 percent holdout data using stratified sampling. Logistic regression, support vector machine, gradient boosting, and random forest were trained using the same eight inputs. Five fold stratified cross validation was used on the training set. Performance was compared using accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve. The selected implementation is deliberately comparative. It does not assume that a complex nonlinear model is intrinsically superior to a more interpretable model.

The MCDM component followed three steps. First, an illustrative AHP vector was specified for the eight criteria, with quality conformity, delivery reliability, capacity adequacy, and food-safety compliance receiving the strongest a priori emphasis. The pairwise matrix was constructed from this vector and returned a consistency ratio of 0.000; because this perfect consistency is a consequence of construction, it must not be interpreted as stakeholder validation. Second, random forest importance was normalised to sum to one, Third, the AHP and normalised random forest vectors were integrated using Equation (1).

$$w_j^H = \alpha w_j^{AHP} + (1 - \alpha)\tilde{I}_j^{Rf}, \alpha = 0.50, \Sigma_j w_j^H \quad (1)$$

with α = 0.50. TOPSIS ranked supplier-level means using the hybrid weights. Robustness was assessed under four scenarios: a 20% increase in the price, quality, or delivery weight, and an equal-weight scenario. Spearman rank correlation and maximum rank shift were used to compare each scenario with the baseline.

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RESULTS AND DISCUSSION

The simulated data show meaningful variation across the operational criteria. Table 2 indicates that mean quality conformity was 89.31, whereas mean delivery reliability was lower at 85.90. The lower average and larger standard deviation of delivery reliability suggest that fulfilment performance is a more volatile operational signal than product quality in the constructed scenario. Capacity adequacy and continuity also varied materially. This matters because selection mechanisms based on a single price comparison would fail to capture the difference between suppliers that are competitively priced and suppliers that can repeatedly fulfil the required volume.

Table 2. Descriptive Statistics of the Synthetic Supplier Month Dataset

Criterion	Mean	SD	Min	Max
Price index	99.26	6.59	82.00	111.86
Quality conformity	89.31	5.70	76.72	100.00
Delivery reliability	85.90	7.48	63.53	100.00
Capacity adequacy	78.69	9.28	53.37	100.00
Continuity score	84.71	8.59	66.49	100.00
Distance (km)	36.64	23.62	3.00	90.41
Food safety compliance	0.96	0.20	0.00	1.00
Traceability score	77.69	13.57	30.00	100.00

Source: (Research Results, 2026)

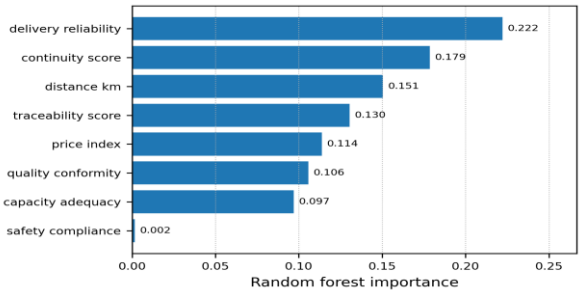
Table 3. Classification Performance on the Synthetic Eligibility Task

Model	CV Accuracy	Test Accuracy	Precision	Recall	F1	AUC
Logistic Regression	0.893 ± 0.072	0.792	0.806	0.784	0.795	0.899
Support Vector Machine	0.887 ± 0.072	0.708	0.735	0.676	0.704	0.855
Gradient Boosting	0.834 ± 0.039	0.764	0.794	0.730	0.761	0.834
Random Forest	0.851 ± 0.032	0.750	0.744	0.784	0.763	0.850

Source: (Research Results, 2026)

Table 3 reports the classification results. Logistic regression achieved the highest holdout accuracy of 0.792, F1 score of 0.795, and AUC of 0.899. The result is substantively important because a parsimonious linear model outperformed the more flexible alternatives on the holdout sample. This finding cautions against presenting model complexity as a proxy for decision quality. In the present simulation, the eligibility process was sufficiently structured for a transparent classifier to perform strongly. Random forest nevertheless achieved the strongest cross validated accuracy among the tree based methods and was retained for feature importance because its nonparametric structure can represent conditional associations that a linear coefficient may understate. This use of model based weights is consistent with emerging ML MCDM architectures, although the structure of the hybridisation must remain visible to end users (Gidiagba et al., 2025).

The model results should not be interpreted as a validation of any real supplier. Classification metrics describe performance against a synthetic label whose logic is known to the study design. Their value is therefore methodological rather than evidentiary: they verify that the pipeline can discriminate a constructed eligibility pattern, compare modelling choices, and produce a reproducible record of how the ranking inputs were generated. Field deployment would require outcome labels based on verified acceptance decisions, delivery receipts, quality inspection records, and food safety documentation. It would also require governance rules for missing values, periodic retraining, and human review of borderline cases.



Source: (Research Results, 2026)
Figure 1. Random Forest Feature Importance

Table 4. AHP, Machine Learning, and Hybrid Criterion Weights

Criterion	AHP	RF Importance	Hybrid
Price index	0.120	0.114	0.117
Quality conformity	0.220	0.106	0.163
Delivery reliability	0.180	0.222	0.201
Capacity adequacy	0.150	0.097	0.123
Continuity score	0.120	0.179	0.149
Distance (km)	0.060	0.151	0.105
Food safety compliance	0.090	0.002	0.046
Traceability score	0.060	0.130	0.095

Source: (Research Results, 2026)

Figure 1 and Table 4 show the movement from model specific importance to a hybrid decision weight. Delivery reliability was the most influential random forest feature with an importance value of 0.222. Continuity, distance, and traceability were also empirically informative. After the hybridisation, delivery reliability received the largest weight at 0.201. followed by quality conformity (0.163) and continuity (0.149). Quality conformity remained prominent because it had the strongest AHP priority even though its random forest importance was lower. This is an intended feature of the architecture: statistical importance informs, but does not erase, explicit normative priorities.

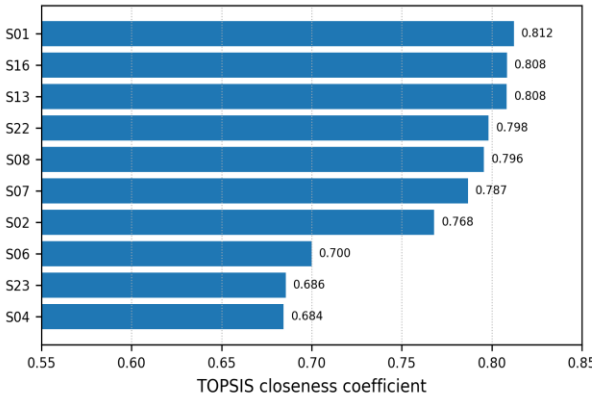
Food safety compliance obtained a low random forest importance because it was nearly constant in the synthetic data. This should not be read as evidence that food safety is unimportant. It identifies a known modelling risk: a legally or ethically nonnegotiable criterion can be statistically uninformative when almost all records meet the requirement. In operational use, such a criterion should be implemented first as a mandatory screening rule and only then included in ranking among eligible suppliers. This distinction between eligibility conditions and compensatory preferences is critical for procurement systems. A model that permits excellent price or delivery scores to compensate for a noncompliant food safety status would be analytically incorrect and institutionally unsafe.

Table 5. Top Ten Supplier Rankings Using Hybrid TOPSIS

Rank	Supplier	Closeness	D+	D-
1	S01	0.812	0.0095	0.0411
2	S16	0.808	0.0096	0.0407
3	S13	0.808	0.0103	0.0436
4	S22	0.798	0.0106	0.0419
5	S08	0.796	0.0109	0.0424
6	S07	0.787	0.0108	0.0397
7	S02	0.768	0.0131	0.0432
8	S06	0.700	0.0149	0.0348
9	S23	0.686	0.0155	0.0338
10	S04	0.684	0.0154	0.0334

Source: (Research Results, 2026)

The hybrid TOPSIS result places Supplier S01 first with a closeness coefficient of 0.812, followed by S16 and S13 (both 0.808 before tie-breaking by the unrounded coefficient) Figure 2 shows that the first six suppliers form a compact high-performing group. Their proximity means that selecting only the displayed top rank would be fragile if uncertainty, contractual capacity, commodity needs, or geography were ignored. A defensible use would treat them as a preferred pool and require documented review of the unrounded scores and operational constraints.



Source: (Research Results, 2026)
Figure 2. TOPSIS Closeness Coefficients for the Top Ten Suppliers

The ranking pattern is aligned with the broader literature on sustainable and resilient supplier selection, which emphasises that cost should be considered alongside quality, delivery, resilience, and compliance attributes (Afrasiabi et al., 2022; Fallahpour et al., 2021; Gokler & Boran, 2023). It also extends the logic of recent ML MCDM studies. Abdulla et al. (2023) use machine learning feature importance to support supplier criterion weights, while Abdulla and Baryannis (2024) argue for explainable hybrid frameworks. The present model adopts the same general principle but frames it specifically for local food procurement and explicitly separates a proof of concept result from a real world procurement decision.

Table 6. Sensitivity Analysis of the Supplier Ranking

Scenario	Rank 1	Rank 2	Spearman rho	Maximum Shift
Price +20%	S16	S01	0.955	8
Quality +20%	S16	S01	0.948	8
Delivery +20%	S16	S01	0.946	8
Equal weights	S13	S22	0.977	4

Source: (Research Results, 2026)

Table 6 reports sensitivity results. The equal weight scenario retained S13 as the first ranked supplier and produced a Spearman correlation of 0.977 with the baseline ranking. When the price, quality, or delivery weight increased by 20 percent, S16 became the leading supplier and the rank correlations remained between 0.946 and 0.955. The stability of the overall order is encouraging, but the movement at the very top is not trivial. It shows

that close alternatives can exchange positions when decision makers revise their priorities. The appropriate conclusion is not that one supplier is universally optimal. Rather, the model makes the consequences of changing priorities explicit and reviewable.

The sensitivity evidence has a practical governance implication. Because sensitivity analysis is a recognised diagnostic for the consequences of MCDM weight changes, the high rank correlations should be read as a robustness signal rather than as a guarantee of a fixed optimum (Demir et al., 2024). The model should be implemented as a staged decision support mechanism rather than as an automatic award engine. Stage one should verify hard eligibility requirements, including food safety documentation and supplier identity. Stage two should calculate a data based performance profile from verified receipts, inspection results, and service records. Stage three should rank eligible suppliers with the agreed MCDM weight configuration. Stage four should require documented human review, especially when the top alternatives have small score differences or when a local producer is affected by a decision. This architecture gives procurement personnel an intelligible record of why alternatives were screened, prioritised, or retained for review.

Data governance is equally central to model quality. Data fields must have a clear source, a defined update frequency, and an auditable correction process. Delivery reliability, for example, should distinguish delay caused by a supplier from delay caused by access constraints, demand changes, or receiving failures. Traceability indicators should not be reduced to a binary upload status when the completeness and usability of records vary. Without such distinctions, a seemingly objective dataset can reproduce measurement error and direct attention away from operational causes. The result is not merely a technical issue. It bears on whether suppliers have a fair opportunity to understand and improve their performance record.

The local food orientation also requires care in interpreting predictive outputs. Small suppliers may have limited digital documentation even when they have reliable product quality and local knowledge. A model that treats missing digital evidence as poor performance can inadvertently privilege firms that are already administratively advantaged. A responsible deployment should therefore accompany the scorecard with capacity building, transparent correction windows, and a supplier development pathway. In this sense, model explainability is not an optional interface feature. It is a condition for contestability, learning, and accountable public procurement. The hybrid approach provides a workable starting point because its criteria, weights, and sensitivity consequences can be examined openly.

Several limitations delimit the interpretation of the study. First, the data and eligibility labels are synthetic, so the statistical findings cannot be generalised to actual MBG suppliers. Second, the AHP priorities were illustrative and were not elicited from procurement officers, nutrition personnel, food safety specialists, or local producer representatives. Third, the model does not include commodity specific perishability, environmental indicators, supplier financial resilience, or spatial equity measures. These limitations do not weaken the value of the computational demonstration, but they identify the empirical work required before the model could support public procurement. A subsequent study should use validated multi site data, co design the criteria with stakeholders, apply a mandatory compliance gate, and evaluate decisions prospectively against verified delivery and quality outcomes.

CONCLUSION

This study developed a reproducible proof of concept for local food supplier selection in the Makan Bergizi Gratis context by integrating machine learning, AHP, and TOPSIS. The synthetic experiment showed that logistic regression achieved the strongest holdout eligibility classification performance, while random forest revealed that delivery reliability, continuity, distance, and traceability were informative features. The hybrid weighting stage preserved the normative priority of quality conformity and translated the combined evidence into an auditable TOPSIS ranking. Sensitivity analysis demonstrated strong overall ranking stability, while also showing that close top ranked suppliers can change position when procurement priorities shift. The model's contribution is therefore not an automatic selection of suppliers, but a structured decision mechanism that makes the relationship between evidence, priorities, and ranking visible. Its use in actual MBG procurement requires validated operational data, stakeholder derived weights, noncompensatory food safety screening, and prospective evaluation

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