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# Development of Vendor Selection Criteria and Its Relationship using Delphi Method, Best Worst Method (BWM) and Structural Equation Modeling-Partial Least Squares (SEM-PLS) in PT PLN UPT Durikosambi

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**Abstract.** An accurate vendor selection process is a critical factor in ensuring the successful execution of construction projects and asset maintenance within PT PLN UPT Durikosambi. This study aims to develop a more objective vendor selection framework using a Multi-Criteria Decision Making (MCDM) approach combined with statistical validation. The research process includes a preliminary study, development of conceptual and operational models, data collection, and analysis and interpretation. Criteria and subcriteria were identified based on existing conditions and relevant literature, then validated through the Delphi method to achieve expert consensus. The weighting of criteria was determined using the Best-Worst Method (BWM), recognized for its high consistency and efficiency in comparisons. The relationships among criteria were further analyzed using the Structural Equation Modeling-Partial Least Squares (SEM-PLS) approach to identify significant influences among variables. The findings of this research are expected to provide a strategic and adaptive foundation for decision-making in the procurement of construction services within PLN units or similar public infrastructure agencies.

**Keywords:** *Vendor Selection, Multi-Criteria Decision-Making, Delphi Method, Best-Worst Method, SEM-PLS.*

## 1 Introduction

PT PLN is responsible for the supply of electricity across Indonesia, covering generation, transmission, and distribution to end users. The reliability of the transmission system is critical to ensure a stable electricity supply. PT PLN UIT JBB (*Unit Induk Transmisi Jawa Bagian Barat*), through its six transmission units, including UPT Durikosambi, supports electricity distribution across West Jakarta, North Jakarta, and Tangerang areas. UPT Durikosambi operate 34 substations, 88 transformers with a capacity of 7,040 MVA, and extensive transmission lines, supported by 164 personnel, committed to maintaining system reliability through asset maintenance and timely project execution.

One critical factor ensuring system reliability is the timely execution of construction services. In practice, inaccurate vendor selection has led to delays in project completion, resulting in amendments, price revisions, and even financial penalties. Data from 2020–2024 show that 52% of projects required amendments, and 1% incurred penalties. These issues often stem from poor vendor planning, lack of experience, equipment delays, and inadequate communication.

Monczka et al. [1] emphasize that improper supplier selection can result in delivery delays, quality degradation, and rising operational costs. Thus, an objective and structured vendor evaluation process is essential. Sun et al. [2] also note that vendor performance often involves qualitative elements and uncertain data, making systematic and logical evaluation methods validated in real-world applications are crucial for decision-making.

Currently, vendor selection at PLN still relies on a binary elimination system based only on price and experience, without in-depth analysis of financial stability or administrative completeness. This creates inconsistencies and limits the reliability of selection outcomes [3]. Therefore, a more comprehensive evaluation tool is needed.

Moreover, existing procurement decision models may no longer be relevant in today's dynamic and complex construction landscape [4]. With the growing diversity of procurement methods, increasing technical challenges, and rising demands for value-for-money, classical indicators such as cost, time, and quality are no longer sufficient. There is an urgent need to update decision models to reflect modern industry principles such as sustainability, digital integration, and strategic vendor development [3].

Therefore, this study aims to develop an enhanced vendor selection model by identifying key criteria, assigning priority weights, and analyzing inter-criteria relationships, to ensure a more objective, reliable, and data-driven vendor evaluation at PT PLN UPT Durikosambi.

## 2 Literature Review

Numerous scholars have developed structured frameworks to enhance the objective and comprehensiveness of vendor selection processes, often by employing multi-criteria decision-making (MCDM) techniques and statistical validation. Literature Review used is presented in Table 1.

Ecer and Pamucar [5] introduced a green supplier evaluation model employing the Fuzzy Best-Worst Method (FBWM), emphasizing environmental considerations such as carbon emissions, energy efficiency, and waste

**Table 1** Literature Review

| No | Author (Year) | Research Focus | Criteria and Sub-Criteria | Tool(s) Used |
|---|---|---|---|---|
| 1 | Ecer & Pamucar (2020) | Development of a sustainable supplier selection model based on the triple bottom line | Economic (Price, Delivery time, Service, Transportation cost, Quality)<br>Environmental (Pollution Control, Environmental Competencies, Green Management, Environmental Cost)<br>Social (Training, Health & Safety, Information Disclosure, Rights of Stakeholders, Employee Rights) | Fuzzy Best-Worst Method (F-BWM), Fuzzy CoCoSo, Bonferroni operator |
| 2 | Tavana et al. (2020) | Sustainable supplier selection in group decision-making based on fuzzy logic | Lean (Lead Time, Safety, Durability, Performance, Prices, Logistics Cost)<br>Agile (Delivery Time, Response to Request, Conformance to Specs, Quality Stability, Capability)<br>Resilient (Safety Stock, Adaptive Capability, Buffer, Surplus Inventory, Responsiveness)<br>Green (Pollution Control, Reduction, Prevention, Protection Plans) | Fuzzy Group Best-Worst Method (FG-BWM), Fuzzy Combined Compromise Solution (F-CoCoSo) |
| 3 | Gupta & Shaikh (2024) | Identification and validation of sustainable supplier selection criteria in the HVAC sector | Delivery (On-time, No Error, Good Condition, Lead Time)<br>Economic (Reliability, Service, Performance History, Cost)<br>Environmental (Customer value, Adaptability, Pollution control, Certifications)<br>Management (Staff skill, Financial status, Structure, Reputation)<br>Quality (Durability, Low Rejection, Standard Compliance, ISO)<br>Service (Responsiveness, Technical Support, Warranty) | Delphi, Fuzzy AHP |
| 4 | Güneri & Deveci (2023) | Evaluation of supplier selection in the defense industry using complex fuzzy data | Technical (Quality, Technology, Product Performance)<br>Financial (Price, Final Use)<br>Social (Sustainability, Agreements, Training Support)<br>Performance (Supplier Experience, Operational Control) | Q-Rung Orthopair Fuzzy Sets, EDAS (Evaluation based on Distance from Average Solution) |
| 5 | Lajimi et al. (2021) | Supplier selection based on multi-stakeholder perspectives | Capabilities (Price, Delivery, Quality, Reserve Capacity, After-Sales Support)<br>Willingness (Communication, Reciprocity, Info Sharing, Long-Term Relationship) | Multi-Stakeholder Best-Worst Method (MS-BWM) |
| 6 | Sun et al. (2021) | Identifying key factors influencing supplier selection decisions | Relationships, Company Management, Cost (Price, Payment Terms), Delivery (Schedule Control, Delivery Management), Quality (QMS, Product Control), Production Management (Environmental Management), Engineering Management, Service | SEM-PLS, Fuzzy TOPSIS |

management. This study underscored the growing relevance of sustainability in supplier selection methods. This study includes criteria and subcriteria as follows: economics (price, delivery time, service, transportation cost, quality), environmental (pollution control, environmental competencies, green management, environmental cost), and social (training, health & safety, information disclosure, rights of stakeholders, employee rights).

Güneri and Deveci [6] proposed a vendor evaluation model for the defense industry using the Q-Rung Orthopair Fuzzy Sets and EDAS (Evaluation based on Distance from Average Solution) methods. Their work primarily addressed technical capability, reliability, and risk management, although it did not incorporate sustainability or administrative compliance as assessment dimensions. This study includes criteria and subcriteria as follows: technical (quality, technology, product performance), financial (Price, Final Use), social (sustainability, agreements, training support), performance (supplier experience, operational control)

Gupta and Shaikh [7] focused on sustainable vendor selection in the HVAC industry by combining the Delphi method and Fuzzy AHP. Their model included economic, environmental, and social criteria, contributing to a more holistic understanding of sustainability. However, the study did not include statistical validation, such as Structural Equation Modeling (SEM), to assess the reliability of constructs. This study includes criteria and subcriteria as follows: delivery (on-time, no error, good condition, lead time), economic (reliability, service, performance history, cost), environmental (customer value, adaptability, pollution control, certifications), management (staff skill, financial, structure, reputation), quality (durability, low rejection, standard compliance, ISO), service (responsiveness, technical support, warranty). social (ethics, trust, disclosure, staff training), and supplier relationship

Lajimi et al. [8] applied the Best-Worst Method (BWM) to determine consistent weights for evaluating supplier performance. While this approach enhanced the reliability of weight determination, the study did not address the integration of evaluation outcomes with subsequent supplier development strategies. This study includes criteria and subcriteria as follows: capabilities (price, delivery, quality, reserve capacity, after-sales support).

Tavana et al. [9] designed a hybrid approach using Fuzzy BWM and Fuzzy CoCoSo to evaluate suppliers within reverse logistics. Although the model successfully addressed decision-making under uncertainty and complexity, it lacked attention to administrative and regulatory compliance, which are essential in public procurement contexts. This study includes criteria and subcriteria as follows: lean (lead time, safety, durability, performance, prices, logistic cost), agile (delivery time, response to request, conformance to apecs, quality stability, capability), resilient (safety stock, adaptive capability, buffer, surplus inventory, responsiveness), and green (pollution control, reduction, prevention, protection plans).

Sun et al. [10] developed a hybrid model combining factor analysis, Structural Equation Modeling (SEM), and Fuzzy TOPSIS to evaluate supplier performance more objectively. The model provided robust construct validation and supplier ranking capabilities. Nonetheless, it did not extend to strategic follow-up actions such as capacity building or performance improvement planning. This study includes criteria and subcriteria as follows: relationships, company management, cost (price, payment terms), delivery (schedule control, delivery management), quality (QMS, product control), production management (environmental management), engineering management, and service.

Although existing studies have made significant contributions to the field of vendor evaluation, several key gaps remain. Most notably, many models conceptualize supplier selection as a one-time decision, without incorporating mechanisms for post-evaluation activities such as supplier development or performance improvement. Additionally, while some frameworks emphasize sustainability or technical aspects, they often overlook other essential dimensions, such as administrative compliance, regulatory adherence, and financial stability. Moreover, limited research combines expert judgment techniques with statistical validation tools, resulting in models that may lack empirical rigor. Therefore, there is a clear need for a comprehensive, empirically validated model that not only encompasses multidimensional evaluation criteria but also aligns with strategic vendor management practices.

## 3 Methodology

This study was conducted through four main stages: preliminary study, model development, data collection and model validation, analysis and interpretation, as well as conclusion and recommendation. The overall flowchart of this study is presented in Figure 1.

### 3.1 Preliminary Study Phase

This phase begins with the formulation of the research background, problem identification, objectives, and scope. A literature review is conducted on supply chain management, vendor selection models, and multi-criteria decision-making methods. The study positions itself in contrast to existing PLN models, which have yet to incorporate sustainability indicators or modern quantitative techniques. The developed indicators are designed to be measurable, contextually relevant, and reflective of PLN's procurement practices.

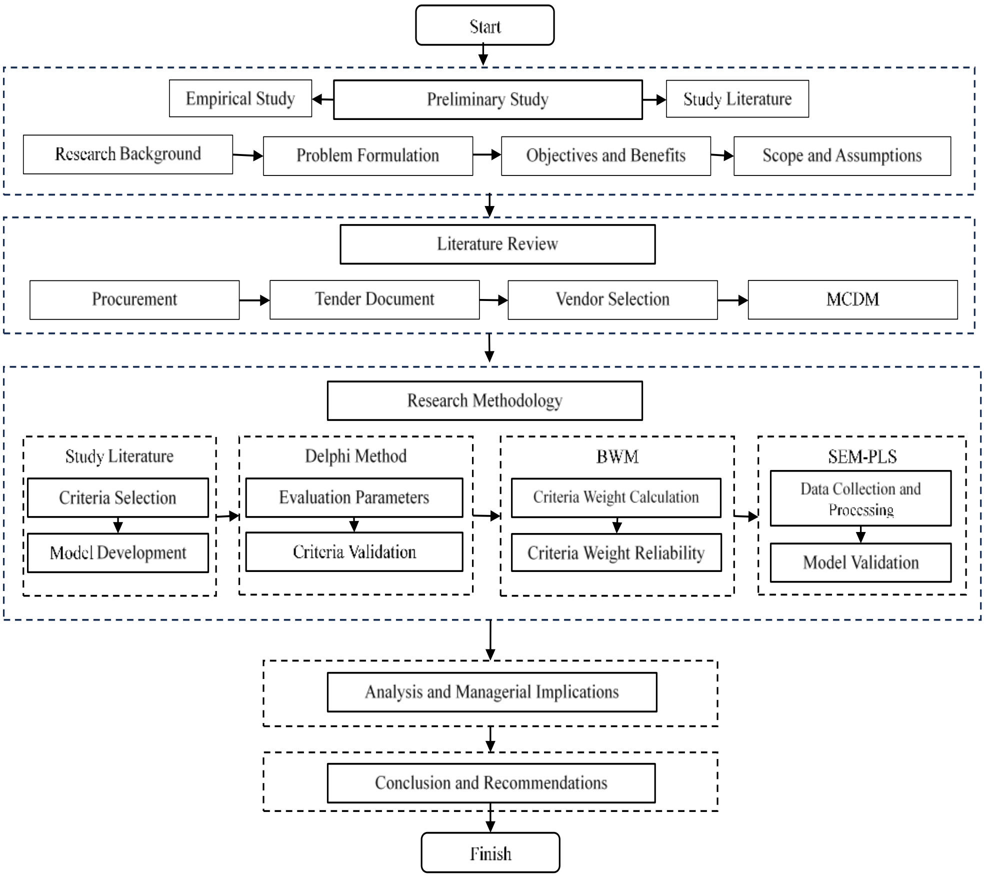


**Figure 1** Research Flowchart

## 3.2 Model Development Phase

The stages of model development carried out include the formulation of a conceptual model and an operational model. The conceptual model is developed based on the research objectives, which are then broken down into main dimensions in the form of criteria and supporting elements that represent them, namely subcriteria. The development of criteria is based on identifying the weaknesses of the existing conditions, as outlined in PT PLN Directors' Regulation Number: 0012.E/DIR/2023 and 0018.P/DIR/2023 regarding the basic principles of procurement. The existing condition criteria consist of four main aspects: administrative, technical, pricing, and regulatory.

These existing conditions were then developed into a proposed model by referring to previous. The developed model is presented in Figure 2.

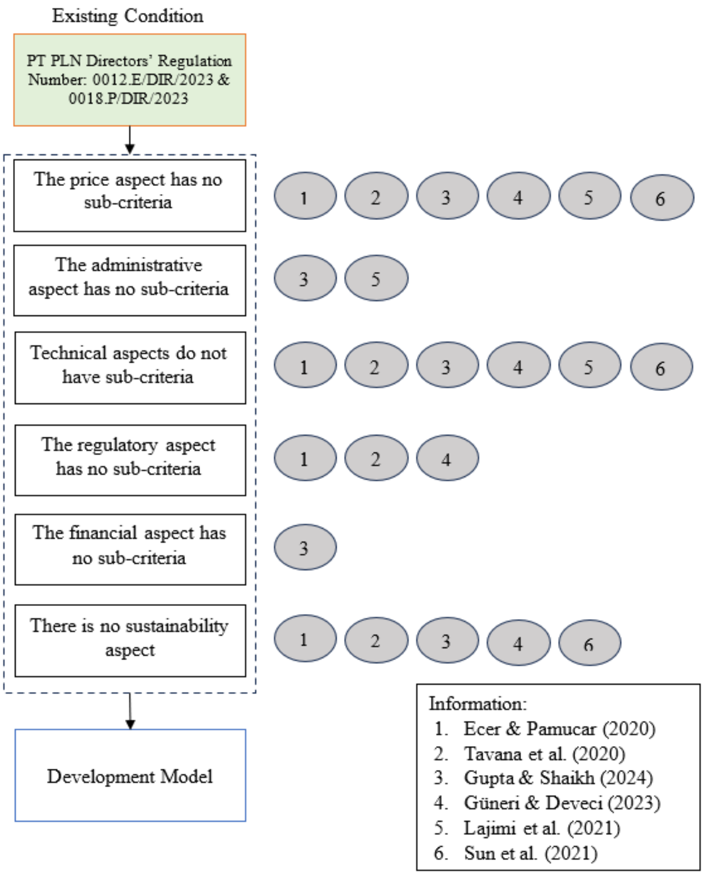


**Figure 2** Criteria Model

Based on the results of the proposed operational model development, the proposed criteria and subcriteria were obtained. Before filtering the criteria and subcriteria, an assessment instrument needs to be prepared through the following steps:

1. Determination of the Rating Scale
   The rating procedure used Likert scale since it is effective for capturing opinions, preferences, expressions, or perceptions from decision-makers.

2. Designing the Assessment Instrument Sheet
   The predetermined scale is then incorporated into a questionnaire form, referred to as the assessment instrument. This instrument is used to collect data through a questionnaire survey method. The collected data will be used to filter the criteria and subcriteria.

### 3.3 Data Collection and Model Validation Phase

Data collection was conducted through the distribution of questionnaires to experts and practitioners with extensive experience and deep understanding of the goods/services procurement process within PT PLN UPT Durikosambi. The steps carried out in the questionnaire distribution process included identifying the target respondents, distributing the research instrument to them, and collecting their responses. The gathered data was then used to validate the criteria and subcriteria using the Delphi method in order to reach a consensus among PLN procurement experts. If a disagreement or lack of consensus occurred, subsequent Delphi rounds were conducted until an agreement on the final criteria and subcriteria was achieved. Advantages of the Delphi Method according to various scholars include:

1. Flexible and adaptive to complex topics.
2. Efficient in gathering expert opinions across geographic locations.
3. Provides strong justification for indicators or variables used in decision-making.
4. Avoids interpersonal influence that may arise in face-to-face discussions
5. Suitable when quantitative data is limited but expert knowledge is needed.

Based on the results of the validation of criteria and subcriteria using the Delphi method, the assessment also involved the application of the Best-Worst Method (BWM) to determine the weights of each criterion. The Best-Worst Method (BWM) is a relatively new multi-attribute decision-making (MADM) method developed [11]. BWM uses two pairwise comparison vectors to determine the weight of criteria. The first vector identifies the *best* criterion meaning the most preferred or most important among all criteria and the second vector identifies the *worst* criterion meaning the least preferred or least important. BWM offers significant advantages, such as better consistency and the ability to derive optimal importance weights.

According to Rezaei [11], the procedure for applying BWM consists of five main steps:
Step 1. A set of decision-making criteria is defined.

Step 2. The decision-maker/expert is asked to determine the best (B) and the worst (W) criteria from the list established in the first step.

Step 3. The decision-maker/expert determines a preference for B over the other criteria using the numbers 1 to 9, where 1 means equally and 9 means very much more important, in a pairwise comparison process. The other numbers are the intermediate evaluations. The result of this step is the vector $A_B = (a_{B1}, a_{B2}, \dots, a_{Bj}, \dots, a_{Bn})$, where $a_{Bj}$ is the preference of criteria B over criterion j .

Step 4. The preferences for the other criteria over the worst criteria are determined using the 1 to 9 scale. The vector $A_w = (a_{1w}, a_{2w}, \dots, a_{jw}, \dots, a_{nw})$ denotes the result of Step 4, where $a_{jw}$ is the preference for criteria $j$ over criteria W .

Step 5. The mathematical model 1 is used to compute the weights of the criteria.

Model 1 :

$$\min \max_j = |w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W| \tag{1}$$

such that

$$\sum_{j=1}^{n} w_j = 1 \;\; w_j \geq 0, \text{ for all j} \tag{2}$$

To determine the weights of the criteria, model 1 can be converted into model 2:

Model 2:

$\min \varepsilon$

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \varepsilon, \text{ for all j} \tag{3}$$

$$\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \varepsilon, \text{ for all j} \tag{4}$$

$$\sum_{j=1}^{n} w_j = 1 \;\; w_j \geq 0, \text{ for all j} \tag{5}$$

A comparison is fully consistent when $a_{Bj} \times a_{jW} = a_{BW}$, for all j, where.
$a_{Bj}$ is the preference of the best criteria over the criteria j.
$a_{jW}$ is the preference of criterion j over the worst criteria.
$a_{BW}$ is the preference of the best criterion over the worst criteria.

According to comparative studies by Mi et al. [3], the Best-Worst Method (BWM) has several advantages over other weighting methods such as AHP, ANP, and Swing Weighting:

1. It requires fewer comparisons, only 2n−3 for *n* criteria, compared to n(n−1)/2 in AHP.
2. It offers higher consistency in assessments by focusing only on the extreme preferences (Best and Worst).

3. It is easier to use for decision-makers unfamiliar with complex methods.It is more stable and accurate in deriving weight.
4. It can be integrated with other methods.

To demonstrate how the developed vendor selection model could be applied in real-world procurement decisions, consider the following hypothetical example. Suppose PLN UPT Durikosambi is planning a major substation refurbishment project and needs to select a vendor from among vendor using the validated criteria and their respective weights obtained through the Best-Worst Method, each vendor would be assessed across multiple dimensions.

The next stage involves testing the relationships among criteria using the Structural Equation Modeling–Partial Least Squares (SEM-PLS) approach. This approach is employed to examine the overall validity of the structural model and to identify significant influences among the predetermined variables/criteria. SEM-PLS is well-suited for analyzing models with relatively small sample sizes and is capable of handling the complexity of relationships among latent variables. The use of SEM-PLS in this study provides an in-depth understanding of how the criteria interact with each other and contribute to the decision-making process for vendor selection.

The evaluation of the model consists of two stages: measurement model validation (outer model) and structural model evaluation (inner model). The validation of the measurement model is conducted by assessing the reliability and validity of the indicators that form the latent variables. In this study, the relationship built between the indicators and their latent variables is a reflective relationship. There are four aspects that need to be considered in a reflective model:

1. Indicator Reliability

Indicator reliability is assessed by examining the correlation coefficient between each indicator and the latent variable. An indicator is considered reliable if the coefficient value is greater than 0.6 [12], which means the indicator reliably reflects the latent construct.

2. Composite Reliability

The composite reliability value is used to measure the internal consistency of a block of indicators. It is recommended that the composite reliability value be greater than 0.6 [12]. Composite reliability can be calculated using the following formula:

$$\rho c = \frac{(\sum_{k\lambda jk})2}{(\sum_{k\lambda jk})2+\sum_{k} var(\varepsilon jk)} \tag{6}$$

3. Convergent Validity

A way to assess the convergent validity of the outer weights is by examining the value of Average Variance Extracted (AVE), which should be greater than 0.5. The AVE value can be calculated using the following formula:

$$AVE = \frac{(\Sigma_{k\lambda jk})2}{(\Sigma_{k\lambda jk})2 + \Sigma_k var(\varepsilon jk)} \quad (7)$$

4. Discriminant Validity

Discriminant validity of the indicators can be assessed through the cross-loading between the indicators and their latent variables. If the correlation between a latent variable and its indicators is greater than the correlations with other latent variables, this indicates that the latent variable better predicts the indicators within its own block than those in other blocks.

In evaluating the structural model, several methods can be used. One common method is evaluating the quality of the structural model through the $R^2$ [13]. Once both the measurement model and structural model evaluations are satisfied, the process continues to the hypothesis testing stage. PLS does not assume a normal data distribution. Instead, it relies on a non-parametric bootstrap procedure to test the significance of the coefficients [12].

Statistical Hypothesis for the Outer Model:

$H_0 : \lambda jk = 0$ (8)

$H_1 : \lambda jk \neq 0$ (9)

Statistical Hypotheses for the Inner Model:

$H_0 : \beta i = 0$ or $H_1 : \gamma i = 0$ (10)

$H_1 : \beta i \neq 0$ or $H_1 : \gamma i \neq 0$ (11)

The test used is the t-test, with the following formulas:

1. For the outer model

$$t_{stat} = \frac{\hat{\lambda} jk}{SE(\hat{\beta} jk)} \quad (12)$$

2. For the inner model (endogenous → endogenous)

$$t_{stat} = \frac{\hat{\beta} jk}{SE(\hat{\beta} jk)} \quad (13)$$

3. For the inner model (exogenous → endogenous)

$$t_{stat} = \frac{\hat{\gamma} jk}{SE(\hat{\gamma} jk)} \quad (14)$$

Where SE (standard error of the estimated parameter) is obtained through the bootstrapping procedure.

Decision rule: Reject $H_0$, if $|t_{stat}| > Z_{\alpha/2} = 1.96$ (15)

According to Hair et al. [12], PLS-SEM is highly flexible, as it does not require strict multivariate assumptions and can handle large models with many indicators. It is particularly ideal for exploratory research aimed at predicting and developing new theories, such as in this study, which seeks to build a vendor selection model based on actual criteria and weights from the field.

All data processing was conducted quantitatively, supported by relevant statistical and modeling software, specifically SmartPLS version 3.0.

### 3.4 Analysis and Interpretation Phase

This stage interprets the weight of each criterion and the interrelationships among variables.

Data collection was conducted through a survey targeting experts and procurement practitioners with experience in the operational environment of PT PLN (Persero) UPT Durikosambi. Respondents were selected using a purposive sampling method to ensure they possessed a thorough understanding of actual procurement practices, vendor evaluation challenges, and the need for a more comprehensive selection system.

The model was developed in three main stages. The first stage involved validating the criteria and subcriteria using the Delphi method. This stage aimed to achieve expert consensus on the relevance and appropriateness of the criteria based on the specific characteristics of procurement within PLN. The initial model referred to the fundamental criteria outlined in PT PLN (Persero) Directors Regulations No. 0012.E/DIR/2023 and 0018.P/DIR/2023, which include price, administrative, technical, financial, and regulatory aspects. However, these regulations lacked a detailed and measurable subcriteria structure. To enhance the model, one additional dimension—sustainability—was introduced, allowing the vendor selection model to align with the broader ESG (Environmental, Social, and Governance) agenda.
The Delphi method was used to achieve expert consensus on the list of evaluation criteria and subcriteria. The process involved:

1. Round 1: Experts provided individual ratings on the relevance and importance of proposed criteria.
2. Round 2: Revised criteria were re-evaluated until at least 80% consensus was achieved.

Once the final set of criteria and subcriteria was established through Delphi, the BWM was applied to assign weightings. Experts were asked to:

1. Identify the most important (Best) and least important (Worst) criteria and subcriteria.
2. Conduct pairwise comparisons of each criterion against Best and Worst, using a scale of 1 to 9.
3. Solve the BWM optimization model to obtain the weight of each criterion.

The final stage employed SEM-PLS to model and validate the relationships between criteria and their impact on vendor selection outcomes. Through SEM-PLS analysis, this study aims to validate the measurement model to ensure that each criterion and its corresponding indicators accurately reflect the underlying constructs. This involves examining factor loading, average variance extracted (AVE), and composite reliability to confirm the reliability and validity of the model. Furthermore, the structural model will be assessed to determine the strength and significance of the relationships between criteria and overall procurement outcomes. A bootstrapping technique will also be employed to enhance the reliability of parameter estimates. Initial Research Model is presented in Figure 3.

The insights gained from this SEM-PLS analysis are expected to provide practical implications for PLN UPT Durikosambi. Specifically, the findings will inform which selection criteria exert the greatest influence on procurement performance, thereby helping managers prioritize focus areas during vendor evaluations. Additionally, the results can guide the refinement of procurement strategies and policies, ensuring that they are more evidence-based, strategic, and aligned with the organization's objectives in managing construction projects.

### 3.5 Conclusions and Recommendations

The final phase presents research conclusions and formulates recommendations for policy improvements. Suggestions are directed at both practical implementation at PLN and future research on model refinement.

## 4 Conclusion

This study developed a more objective and measurable vendor selection model for PT PLN UPT Durikosambi by integrating a MCDM approach with statistical validation. The process began with the identification of criteria and subcriteria based on existing conditions and literature review, which were then validated using the Delphi method to reach expert consensus. The weighting of the criteria was determined using BWM, which proved to be efficient and consistent. Furthermore, the relationships between the criteria were analyzed using SEM-PLS approach to understand the significant influences among variables.

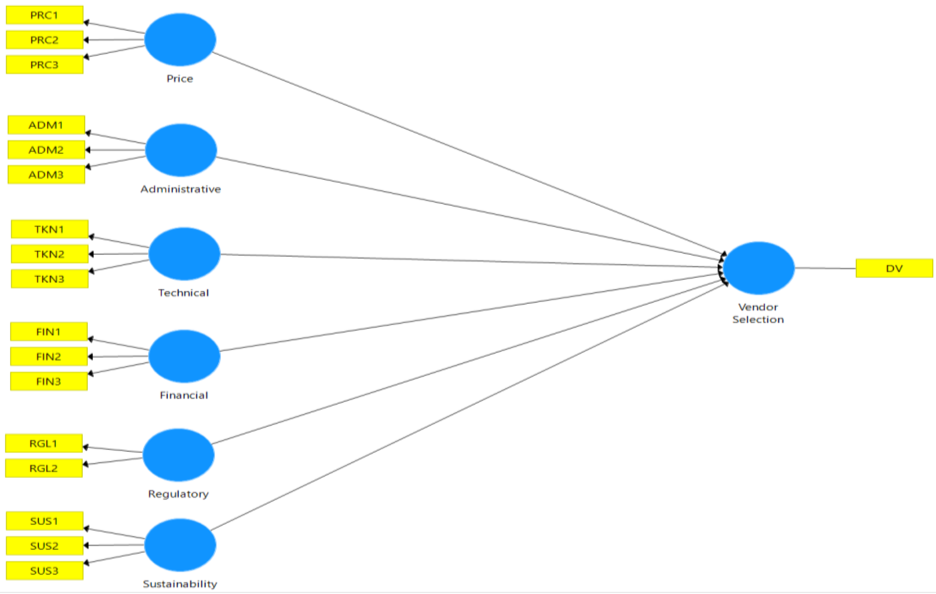


**Figure 3** Initial Research Model

Furthermore, while this study was specifically conducted at PLN UPT Durikosambi, the proposed vendor selection model based on validated multi-criteria decision-making and empirical structural relationships holds significant potential for broader application. With minor adjustments to account for local procurement contexts and operational characteristics, this model could be scaled and adapted for use in other PLN units or similar public infrastructure agencies. Such scalability would support the wider adoption of more objective and data-driven procurement practices across the organization.

This model not only considers price, administrative, technical, and financial aspects but also incorporates regulatory and sustainability principles. Therefore, it can serve as a strategic and adaptive foundation for making more accurate, consistent, and responsible decisions in construction service procurement.

To facilitate scalability, future efforts may focus on customizing certain criteria or weights based on local conditions, regulatory frameworks, and project types. This would enable broader organizational learning and foster the adoption of more evidence-based procurement strategies across PLN's national network.

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