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A Novel MPSI Weighting and Proximity Indexed Value Framework for Multi-Criteria Selection of Marketplace Logistics Partners

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Logistics Partner Selection; Multi-Criteria Decision Making; MPSI Method; PIV Method; Sensitivity Analysis;

ABSTRACT

In facing the increasingly intense competition in the logistics industry, companies are often confronted with challenges in selecting the most appropriate logistics partner due to the many performance criteria that must be considered simultaneously. This study aims to evaluate and determine the best logistics partner using a Multi-Criteria Decision-Making approach through the integration of the MPSI method for criteria weighting and PIV for the alternative ranking process. The criteria used include Transit Time, On-Time Delivery, First-Attempt Success, Attempt Rate, and Package Volume, which are analyzed based on the performance data of each alternative. The weighting results indicate that Package Volume and Transit Time are the most dominant factors in the evaluation process. Based on the PIV method calculations, the ranking results were obtained, with NJ Logistics Partner occupying the first rank with a score of 0.46408, followed by TK Logistics Partner in second place with a score of 0.44014, and JT Logistics Partner in third place with a score of 0.39282. Sensitivity tests through various weight change scenarios showed that the ranking structure remained consistent, indicating that the model has a high level of stability and resilience to parameter variations. Overall, the proposed approach is able to produce decisions that are objective, measurable, and reliable as a basis for supporting strategic logistics partner selection.

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I. Introduction

The growth of marketplaces in recent years has been very rapid, driven by changes in consumer behavior who increasingly rely on digital transactions to meet daily needs[1]. E-commerce platforms are no longer just simple buying and selling places, but have developed into ecosystems that integrate various services such as digital payments, data-driven promotions, and real-time inventory management. In Indonesia, the emergence of major players like Tokopedia, Shopee, and Bukalapak has tightened competition while also expanding market reach to areas that were previously difficult to reach by conventional retail[2]. This growth brings direct consequences to the logistics system, which must be able to handle surges in order volume with increasing speed and accuracy. The complexity of logistics rises due to the need for managing multi-location warehouses, optimizing delivery routes, integrating with various courier partners, as well as demands for transparency in product tracking by consumers[3]. Additionally, the wide variety of products, ranging from everyday necessities to high-value electronic products, requires different handling and distribution standards. This challenge becomes even more apparent during seasonal demand spikes, such as during major promotional periods, which test the readiness of technology infrastructure and the overall distribution network. These developments indicate that the success of a marketplace is not only determined by marketing strategies and the number of users, but also by the ability to manage a logistics system that is increasingly dynamic and fully integrated.

The importance of choosing the right logistics partner is increasingly felt amid the growing competition in marketplaces and the continuously rising customer expectations[4]. Delivery speed, punctuality, and the condition of goods upon receipt are factors that greatly impact the overall shopping experience. When logistics partners are able to work consistently and responsively, customer trust in the platform will also grow, thereby increasing the likelihood of repeat purchases. Conversely, delays, shipping errors, or poor handling of goods can quickly damage the company's reputation in the eyes of consumers. From an operational perspective, choosing the optimal partner also plays a role in controlling distribution costs, minimizing returns, and improving supply chain efficiency. Good system integration between the marketplace and logistics providers enables real-time tracking, accurate management of shipping data, and information-based decision making[5]. Therefore, the logistics partner selection process cannot be done carelessly, but needs to consider various criteria such as service performance, territorial coverage, distribution capacity, and cost stability in order to achieve a balance between customer satisfaction and operational efficiency.

The challenge of subjectivity in weighting evaluation criteria often arises when the process of determining weights relies more on individual judgment or the preferences of decision-makers[6]. Each evaluator usually has different perspectives, experiences, and

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interests, so perceptions of the importance level of a criterion may not be the same. In the context of selecting a logistics partner, for example, some parties may consider delivery speed as the most crucial factor, while others place more emphasis on cost or distribution coverage. These differences can result in inconsistent weights and potentially affect the final ranking of alternatives. In addition, subjectivity can also lead to unconscious bias, especially if decisions are made without a strong data foundation or without a structured weighting method[7]. When the weights change even slightly, the evaluation results can shift significantly, casting doubt on the stability of the decisions. This condition highlights the need for a more systematic and measured approach in determining weights, so that the evaluation process becomes more objective, transparent, and accountable.

The need for a decision support system (DSS) based on an objective and quantitative approach is becoming increasingly urgent amid the complexity of decision-making that involves many criteria and alternatives[8], [9]. In situations such as selecting a logistics partner or evaluating marketplace performance, decisions are no longer sufficient by relying solely on intuition or experience. A system is needed that can process data in a structured manner, calculate criteria weights rationally, and produce alternative rankings based on calculations that can be verified. Quantitative approaches help minimize personal bias, as each decision is based on numerical values and clear formulas. In addition, DSS designed with an objective method allows the evaluation process to be more transparent and consistent, even when carried out by different teams. Such systems also facilitate scenario simulations, enabling decision-makers to see the impact of changes in weights or data on the final outcomes[10], [11]. Ultimately, the implementation of DSS based on an objective and quantitative approach provides a stronger foundation for making strategic decisions that impact operational performance and customer satisfaction.

The DSS model based on the integration of modification preference selection index (MPSI) and proximity indexed value (PIV) is designed to provide a more structured and measurable logistics partner evaluation process. MPSI plays a role in determining the weight of criteria objectively based on data characteristics, thus minimizing the influence of subjectivity from the early stages[12]. Subsequently, PIV is used to rank alternatives through a comparative approach that considers deviations of values from ideal conditions, making the final results more stable against data variations[13]. The integration of these two methods allows the system to operate systematically, from processing raw data to producing final recommendations that can be mathematically justified. With this framework, the evaluation of logistics partners no longer relies solely on intuition, but rather on transparent quantitative calculations. In addition, this model is also designed to test the consistency of results through an analysis of weight and ranking comparisons, so it can be determined whether the decisions produced remain aligned when there are small changes in parameters. Sensitivity

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testing is also conducted to see the extent to which changes in criteria weights affect the ranking positions of alternatives, allowing the stability level of the model to be measured clearly. This approach provides a stronger basis for decision-makers in determining the logistics partner that best suits operational needs and expected service standards.

The contribution of this research lies in the integration of objective weighting using MPSI with a proximity-based ranking approach through PIV within a unified decision-making framework. This combination presents an evaluation mechanism that is not only capable of determining criteria weights based on data but also produces alternative rankings based on their proximity to the ideal solution more stably. In addition, this study develops a DSS framework specifically designed to support the logistics partner selection process in the marketplace ecosystem, making it practically applicable in real operational contexts. The framework is systematically structured, starting from the stage of identifying criteria, the process of normalization and weighting, to the calculation of the final preference values. Not stopping at the ranking stage, this study also involves sensitivity analysis to examine the extent to which changes in weights affect the position of alternatives in the ranking list. This step is important to ensure that the proposed model is not only accurate but also has a good level of consistency and resilience against parameter fluctuations. Overall, this contribution enriches the development of multi-criteria-based DSS methods with a more objective, integrated, and applicable approach to marketplace logistics partner selection.

II. Related Work

Research related to the selection of logistics partners in the context of e-commerce has developed rapidly along with the increasing complexity of supply chains and rising service demands. Various multi-criteria decision making (MCDM) approaches are widely used to assist the evaluation process because they can systematically and measurably consider several conflicting criteria. This section reviews several previous studies that serve as the conceptual and methodological foundation in the development of a logistics partner selection model based on DSS.

A study by [14] applied a hybrid MCDM approach that combines the ENTROPY and CRITIC methods for criteria weighting, then the utility is determined using ARAS to rank 3PL providers. The results show that this hybrid approach provides a more consistent and reliable solution, and the most optimal 3PL is chosen based on the data analyzed in the case study. Sensitivity analysis in the model shows the stability of rankings even when the criteria weights change. Research from [15] builds an MCDM model combining F-AHP and TOPSIS to help logistics aggregators choose the most suitable 3PL. F-AHP is used to calculate the criteria weights, while TOPSIS ranks the 3PL alternatives. This study also involves sensitivity analysis to measure the stability of the model, showing that

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the developed model can assist companies in making decisions more objectively.

Research from [16] evaluates logistics service provider options for e-commerce companies with an integrative GRA–TOPSIS approach. Criteria such as distribution costs, delivery time, and operational capacity are analyzed using MCDM to determine the best service provider. A study by [17] used a combination of BWM (Best-Worst Method) and CoCoSo methods to evaluate 3PL providers in the context of last-mile delivery, one of the key issues in e-commerce. The weights of criteria such as cost distribution, timeliness, service flexibility, IT capability, and customer satisfaction were calculated and resulted in stable rankings of 3PL alternatives through sensitivity analysis.

Based on the literature review, it appears that most studies on logistics partner selection still focus on the integration of weighting methods such as ENTROPY, CRITIC, F-AHP, or BWM with ranking techniques such as ARAS, TOPSIS, GRA, or CoCoSo, which are generally applied in the context of 3PL or last-mile delivery in general. Although these hybrid approaches have shown consistent and relatively stable results through sensitivity analysis, most studies have not specifically developed an integrated DSS framework designed specifically for the needs of logistics partner selection in marketplace ecosystems that have dynamic, multi-actor, and digital platform-based characteristics. In addition, the use of objective weighting methods such as MPSI combined with a proximity-based ranking approach like PIV is still very limited in the context of evaluating e-commerce logistics partners. In fact, the integration of MPSI and PIV has the potential to offer a higher level of objectivity and ranking stability because the weighting is entirely data-driven and the ranking process considers the relative closeness to the ideal value more comprehensively. Therefore, there is a research gap in developing a marketplace logistics partner selection model that combines MPSI and PIV within a systematic DSS framework, while also testing its consistency and sensitivity to ensure the reliability of decision outcomes.

III. Methodology

Research methodology is essentially a systematic framework that explains the steps, approaches, and procedures used to answer research questions or achieve study objectives. It encompasses the selection of methods, data collection techniques, the analysis process, and the way of drawing logical and accountable conclusions. Methodology functions not only as a technical guide but also as a scientific foundation that ensures research is conducted in a structured and consistent manner. Its main goal is to produce findings that are valid, reliable, and relevant to the issues being studied, while also making it easier for other researchers to understand, replicate, or develop the research in the future.

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3.1. Research Framework

A research framework is a conceptual framework that depicts the flow of research thinking systematically, from problem identification to the achievement of predetermined goals. This framework shows the relationships between variables, the stages of analysis, and the methods used in the research process, so that readers can understand the direction and structure of the study comprehensively[6]. Through a research framework, each research step is arranged logically so that it does not proceed separately, but rather is interconnected within a complete design. With this framework, the research process becomes more directed, consistent, and easy to evaluate both methodologically and in terms of its scientific contribution, as shown in Figure 1, which represents the research framework of this study.

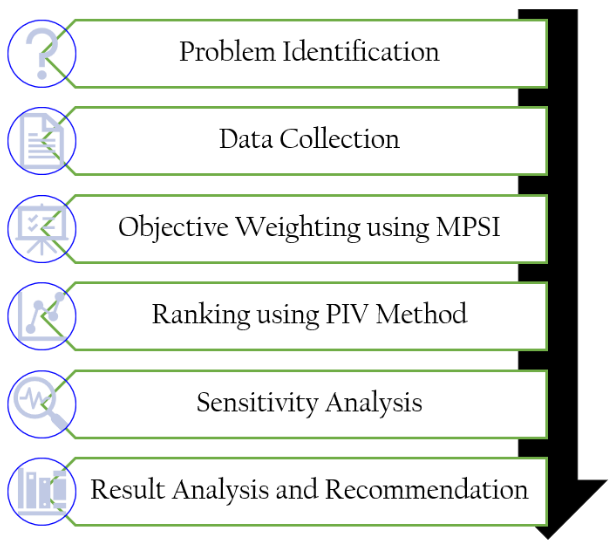

Figure 1. Research Framework

This research begins with the problem identification stage to understand the issues in the process of selecting marketplace logistics partners, which still faces challenges of subjectivity and instability in decision outcomes. Once the problem is clearly defined, the data collection stage is conducted by gathering quantitative data from each logistics partner alternative based on the established evaluation criteria. Next, objective weighting using MPSI is applied to calculate the weight of each criterion based on data, thereby minimizing the influence of subjectivity. The obtained weights are then used in the ranking stage using the PIV method, where each alternative is assessed based on its closeness to the ideal solution to produce a more stable and rational ranking. To ensure the reliability of the model, a sensitivity analysis is conducted to test the consistency and changes in ranking if there are variations in the criteria weights. The final stage, which is result analysis and recommendation, aims to interpret the calculation results comprehensively and provide recommendations for

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the logistics partner that best suits the operational needs of the marketplace.

3.2. Modification Preference Selection Index Weighting

MPSI is an objective weighting method in the MCDM approach that determines the importance level of criteria based on the characteristics and distribution of alternative data, rather than on the subjective assessment of the decision maker[18]. Its basic principle is to measure the variation of each criterion's values to see how much they contribute to differentiating alternatives, so that criteria with higher discrimination levels will receive greater weight. This approach makes the weighting process more rational and based on actual data. One of the main advantages of MPSI is its ability to reduce the subjectivity bias that often occurs in expert comparison-based methods[19]. Additionally, its calculation is relatively simple and easy to implement in decision support systems without requiring complex iterative processes. MPSI also tends to produce stable weights when the data experiences small changes.

The MPSI procedure starts with constructing a decision matrix as shown in equation (1), which systematically presents the performance scores of each alternative across all criteria. This is followed by a normalization step using equation (2) to transform the original data into a uniform scale, ensuring that differences in measurement units do not bias the analysis. Once the normalized matrix is obtained, the mean value of each criterion is computed using equation (3) to serve as a reference point for assessing data spread. Subsequently, preference variation is determined through equation (4), reflecting how far each value deviates from its criterion mean and indicating the discriminating capability of each criterion. These variation results are then applied to establish the relative importance of the criteria. Finally, the weights are derived using equation (5), producing proportional values that can be utilized in subsequent evaluation stages. This structured process guarantees that the weighting mechanism remains objective and grounded in the quantitative characteristics of the dataset.

$$X = [x_{ij}]_{mxn} \tag{1}$$

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{\max_j x_{ij}}; benefit \\ \dfrac{\min_j x_{ij}}{x_{ij}}; cost \end{cases} \tag{2}$$

$$\vartheta_j = \frac{\sum_{i=1}^{m} r_{ij}}{m} \tag{3}$$

$$p_j = \sum_{i=1}^{m} (r_{ij} - \vartheta_j)^2 \tag{4}$$

$$w_j = \frac{p_j}{\sum_{j=1}^{n} p_j} \tag{5}$$

The weighting results using MPSI show that each criterion obtains a weight value that reflects its level of contribution in distinguishing alternatives objectively. These weights become the main basis in the

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subsequent ranking process because they have been calculated based on actual and measurable data variations. Thus, the MPSI weight results provide a more rational and stable foundation to support decision-making in the next evaluation stage.

3.3. Proximity Indexed Value

PIV is a ranking method in the MCDM approach that evaluates alternatives based on their closeness to the ideal value while considering the relative distance of each criterion. This method operates through the process of normalization and calculation of the deviation of alternative values from the best condition, thereby producing a preference index that reflects the position of each alternative comparatively. One of the main advantages of PIV lies in its ability to provide stable ranking results because it is not overly sensitive to extreme changes in a single criterion. In addition, its calculation procedure is relatively simple and transparent, making it easy to integrate into a quantitative-based decision support system. PIV is also effective in handling combinations of benefit and cost-type criteria simultaneously, making it suitable for evaluating logistics partners that involve many performance indicators of different types.

The stages of the PIV method begin with the normalization process to equalize the scale of each criterion so that they can be compared proportionally, which is calculated using (6). Next, the results of the normalization are multiplied by the weights of each criterion to obtain the weighted decision matrix, which is calculated using (7). The next stage is the calculation of the weighted asymptotic index to measure the deviation of each alternative from the ideal reference value, which is calculated using (8). Finally, the final index score is determined to produce the ranking order of alternatives based on their relative closeness, which is calculated using (9).

$$d_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} {x_{ij}}^2}} \tag{6}$$

$$V_{ij} = w_j * d_{ij} \tag{7}$$

$$u_{ij} = \begin{cases} V_{max} - V_{ij}; benefit \\ V_{ij} - V_{min}; Cost \end{cases} \tag{8}$$

$$P_i = \sum_{j=1}^{n} u_{ij} \tag{9}$$

The results of the calculation using the PIV method show the order of alternatives based on their closeness to the predetermined ideal solution. The obtained index values reflect the relative performance of each logistics partner comprehensively against all evaluation criteria. The final ranking produced by PIV can be used as a basis for recommendations in determining the best alternative more objectively and measurably.

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IV. Result and Discussion

Selection of Marketplace Logistics Partners Using the MPSI Weighting and Proximity Indexed Value Method within the Framework of a Decision Support System is an integrated approach designed to help marketplaces determine logistics partners more objectively, systematically, and data-driven. This model utilizes MPSI as an objective weighting method to calculate the importance level of each criterion based on actual data variations, thereby minimizing the influence of subjectivity in the evaluation process. The resulting weights are then used in the PIV method to rank alternatives based on their closeness to the ideal solution, producing a more stable and rational order of logistics partners. All of these stages are integrated into the DSS framework so that the process of data processing, calculations, and final recommendations can be carried out in a structured and transparent manner. This approach not only takes into account various criteria but also provides a sensitivity analysis mechanism to test the consistency of results when there are changes in weights. By combining objective weighting and value proximity-based ranking, this model offers a solution that is more adaptive to the operational dynamics of the marketplace. Ultimately, the developed system is able to provide recommendations for the best logistics partners that align with the strategic needs and service standards of the marketplace sustainably

4.1. Problem Identification

The problem identification stage in this study starts from the reality that the selection of logistics partners in marketplaces is often based on practical considerations, previous experience, or subjective perceptions of service provider performance. Amid the increasing growth of e-commerce transactions, marketplaces face demands for delivery speed, punctuality, and consistent service quality that can no longer be handled solely with an intuitive approach. The abundance of logistics companies with different performance characteristics—ranging from delivery time, operational capacity, success rate of deliveries, to distribution reach—makes the selection process increasingly complex. Without a structured evaluation framework, the decisions made risk being suboptimal and can directly affect customer satisfaction as well as the operational efficiency of the platform.

In addition, the main challenge that arises is the subjectivity in determining the importance weights of each evaluation criterion, which can ultimately affect the ranking results of alternatives. Small changes in the assessment or criteria weights often result in significant shifts in rankings, therefore the stability of the decision is questionable. This situation indicates the need for an approach that can process logistics partner performance data objectively and systematically, while also providing a mechanism to test the consistency of results. Therefore, this study identifies the need for a decision-making model based on quantitative methods integrated within a Decision Support System

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framework, so that the logistics partner selection process can be carried out more rationally, transparently, and accountably.

4.2. Data Collection

The data collection stage was conducted to obtain relevant quantitative information regarding the performance of each logistics partner considered as an alternative in this study. The data collected included several key indicators commonly used in the evaluation of e-commerce logistics services, such as average delivery time (transit time), on-time delivery percentage, first-attempt delivery success rate, delivery attempt rate, as well as operational capacity represented by the estimated daily package volume. All data were obtained from e-commerce logistics industry reports, company performance publications, and publicly accessible market statistics sources. The selection of these criteria was made by considering their relevance to the operational needs of the marketplace, particularly in maintaining service quality and customer satisfaction.

The data collection process was also carried out by ensuring that each alternative has values for all the predetermined criteria, so that the decision matrix can be formed completely without any data gaps. The collected data was then organized in a table format to facilitate normalization and calculation processes in the weighting and subsequent ranking stages. The validity and consistency of the data were re-checked to ensure they corresponded to the operational context of each logistics company and the conditions of the Indonesian e-commerce market. The complete results of this data collection process are presented in Table 1 as a basis for further analysis.

Table 1. Data Collection

Alternative	Transit Time	On-Time Delivery	First-Attempt Success	Attempt Rate	Package Volume
LP Logistics Partner	1.39	97.4	95.2	99.5	1600
TK Logistics Partner	1.05	98	97.4	99.6	500
NJ Logistics Partner	1.48	97	97	96.4	300
PI Logistics Partner	2.06	96.5	94.8	99.2	2000
SC Logistics Partner	2.5	92	90	97.8	800
JE Logistics Partner	1.7	96	95.5	98.3	1200
JT Logistics Partner	1.9	95.8	94	95.3	500

Overall, the data presented in Table 1 shows a fairly significant variation in performance among alternative logistics partners for each evaluation criterion. Differences in transit time, on-time delivery rate, first delivery success, attempt rate, as well as package volume capacity provide a comprehensive picture of the operational characteristics of each alternative. This variation serves as an important basis in the process of objective weighting and ranking, as each criterion contributes differently in distinguishing the performance of logistics partners. With a complete and measurable decision matrix in place, the next stage of analysis can be carried out systematically

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using the MPSI and PIV methods to produce more rational and stable recommendations.

4.3. Objective Weighting using MPSI

Objective weighting using MPSI in this study is used to determine the importance level of each criterion objectively based on the characteristics of the data that have been collected. This approach emphasizes the distribution and variation of values among alternatives, so that the resulting weights truly reflect the ability of each criterion to differentiate the performance of logistics partners. By utilizing the numerical information available in the decision matrix, the MPSI method is able to reduce reliance on subjective assessments or individual preferences that often influence evaluation results. The weights obtained not only represent the relative contribution level of each criterion but also serve as the main foundation in the subsequent ranking process. The advantage of this approach lies in its data-driven nature, making it more adaptive to changes in operational conditions and the dynamics of the e-commerce logistics market.

The MPSI procedure begins with constructing a decision matrix using (1), which systematically presents the performance values of each alternative against all evaluation criteria. The results of the decision matrix are shown as follows.

$$X = \begin{bmatrix} 1.39 & 97.4 & 95.2 & 99.5 & 1600 \\ 1.05 & 98 & 97.4 & 99.6 & 500 \\ 1.48 & 97 & 97 & 96.4 & 300 \\ 2.06 & 96.5 & 94.8 & 99.2 & 2000 \\ 2.5 & 92 & 90 & 97.8 & 800 \\ 1.7 & 96 & 95.5 & 98.3 & 1200 \\ 1.9 & 95.8 & 94 & 95.3 & 500 \end{bmatrix}$$

The next stage is the normalization process using (2), which aims to convert the original data into a uniform scale so that differences in measurement units do not affect the analysis results. The normalization results are presented in Table 2.

Table 2. Normalization Results Using MPSI Weighting

Alternative	Transit Time	On-Time Delivery	First-Attempt Success	Attempt Rate	Package Volume
LP Logistics Partner	0.5560	0.9939	0.9774	0.9990	0.8000
TK Logistics Partner	0.4200	1.0000	1.0000	1.0000	0.2500
NJ Logistics Partner	0.5920	0.9898	0.9959	0.9679	0.1500
PI Logistics Partner	0.8240	0.9847	0.9733	0.9960	1.0000
SC Logistics Partner	1.0000	0.9388	0.9240	0.9819	0.4000
JE Logistics Partner	0.6800	0.9796	0.9805	0.9869	0.6000
JT Logistics Partner	0.7600	0.9776	0.9651	0.9568	0.2500

After obtaining the normalized matrix, the average value of each criterion is calculated using equation (3), and the results are displayed in Table 3.

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Table 3. Average Result of Criteria Using MPSI Weighting

Transit Time	On-Time Delivery	First-Attempt Success	Attempt Rate	Package Volume
0.219515	0.002414	0.003786	0.001636	0.607143

Next, the preference variation is determined through equation (4), which describes the degree of deviation of each alternative's value from its criterion average. The results of this preference variation calculation are presented in Table 4.

Table 4. Preference Variation Results Using MPSI Weighting

Transit Time	On-Time Delivery	First-Attempt Success	Attempt Rate	Package Volume
0.6903	0.9806	0.9737	0.9841	0.4929

The final stage in the MPSI procedure is determining the criteria weights using equation (5), where the obtained variation values are converted into proportional weights. The final weighting results are shown in Table 5.

Table 5. Results of Criteria Weights Using MPSI Weighting

Transit Time	On-Time Delivery	First-Attempt Success	Attempt Rate	Package Volume
0.2631	0.0029	0.0045	0.0020	0.7276

The results of weighting the criteria using the MPSI method in Table 5 show that Package Volume has the highest weight of 0.7276, making it the most dominant factor in determining the evaluation results. This value indicates that the variation in package volume data is much larger compared to other criteria, thus its contribution in distinguishing alternatives is very significant. Transit Time ranks second with a weight of 0.2631, which means that delivery speed still has an important influence, although not as much as package volume. Meanwhile, First-Attempt Success with a weight of 0.0045, On-Time Delivery at 0.0029, and Attempt Rate at 0.0020 have relatively very small values, indicating that these three criteria tend to have more homogeneous data variations, so their distinguishing power among alternatives is not very strong.

4.4. Ranking Alternative using PIV Method

Ranking using the PIV method is carried out by integrating the normalized decision matrix with the weights of the criteria from previous calculations to obtain the preference value of each alternative comprehensively. In this approach, each performance value is compared based on its deviation from the best value in each criterion, thereby indicating how far an alternative-deviates from the most desired condition. These deviation values are then multiplied by the criteria weights to reflect their relative importance, and then summed to produce a final score that serves as the basis for ranking. Alternatives with the smallest total deviation value indicate a closer proximity to the ideal solution and are placed at the top rank, while alternatives with larger deviation values occupy the subsequent positions. Through this

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mechanism, the PIV method not only considers the magnitude of performance values, but also the sensitivity of each criterion in differentiating alternatives, so that the resulting ranking is more proportional and consistent with the characteristics of the analyzed data.

The stages of the PIV method begin with the normalization process to equalize the scale of each criterion so that they can be compared proportionally using equation 6, and the results of this normalization are presented in Table 6.

Table 6. Normalization Results Using PIV Method

Alternative	Transit Time	On-Time Delivery	First-Attempt Success	Attempt Rate	Package Volume
LP Logistics Partner	0.2949	0.3830	0.3793	0.3836	0.5266
TK Logistics Partner	0.2228	0.3854	0.3880	0.3840	0.1646
NJ Logistics Partner	0.3140	0.3814	0.3865	0.3717	0.0987
PI Logistics Partner	0.4370	0.3795	0.3777	0.3825	0.6583
SC Logistics Partner	0.5304	0.3618	0.3586	0.3771	0.2633
JE Logistics Partner	0.3607	0.3775	0.3805	0.3790	0.3950
JT Logistics Partner	0.4031	0.3767	0.3745	0.3675	0.1646

Next, the normalized values are multiplied by the weight of each criterion to form a weighted decision matrix calculated using equation 7. This weighted matrix serves as the basis for measuring deviations from the ideal condition, and the results are presented in Table 7.

Table 7. Weighted Normalization Results Using PIV Method

Alternative	Transit Time	On-Time Delivery	First-Attempt Success	Attempt Rate	Package Volume
LP Logistics Partner	0.07757	0.00111	0.00172	0.00075	0.38317
TK Logistics Partner	0.05860	0.00111	0.00176	0.00075	0.11974
NJ Logistics Partner	0.08259	0.00110	0.00175	0.00073	0.07184
PI Logistics Partner	0.11496	0.00110	0.00171	0.00075	0.47896
SC Logistics Partner	0.13952	0.00105	0.00163	0.00074	0.19158
JE Logistics Partner	0.09487	0.00109	0.00173	0.00074	0.28737
JT Logistics Partner	0.10603	0.00109	0.00170	0.00072	0.11974

The next stage is the calculation of the weighted asymptotic index to measure the degree of deviation of each alternative from the ideal reference value, calculated using equations 8 and 9. The results of the weighted asymptotic index calculations are shown in Table 8.

Table 8. Weighted Asymptotic Index Results Using PIV Method

Alternative	Transit Time	On-Time Delivery	First-Attempt Success	Attempt Rate	Package Volume
LP Logistics Partner	0.06195	0.00001	0.00004	0.00000	0.09579
TK Logistics Partner	0.08092	0.00000	0.00000	0.00000	0.35922
NJ Logistics Partner	0.05692	0.00001	0.00001	0.00002	0.40711
PI Logistics Partner	0.02455	0.00002	0.00005	0.00000	0.00000
SC Logistics Partner	0.00000	0.00007	0.00013	0.00001	0.28737
JE Logistics Partner	0.04465	0.00002	0.00003	0.00001	0.19158
JT Logistics Partner	0.03348	0.00003	0.00006	0.00003	0.35922

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In the final stage, the final index score is determined to produce a ranking of alternatives based on their relative closeness to the ideal solution, as calculated using equation 10. The final alternative index score results are presented in Table 9.

Table 9. Final Index Results Using PIV Method

Alternative	Final Value
LP Logistics Partner	0.15778
TK Logistics Partner	0.44014
NJ Logistics Partner	0.46408
PI Logistics Partner	0.02462
SC Logistics Partner	0.28759
JE Logistics Partner	0.23629
JT Logistics Partner	0.39282

Based on the final calculation of the PIV method, the preference index values obtained for each alternative are then used as the basis for compiling a comprehensive ranking order. Alternatives with the smallest total deviation value or the highest closeness index to the ideal solution are placed at the top position, while alternatives with larger values are positioned next according to the quantitative evaluation results. This process produces a ranking structure that objectively reflects the relative performance of each logistics partner and is consistent with the criteria weights previously determined. The final results of the alternative ranking are presented in Figure 2.

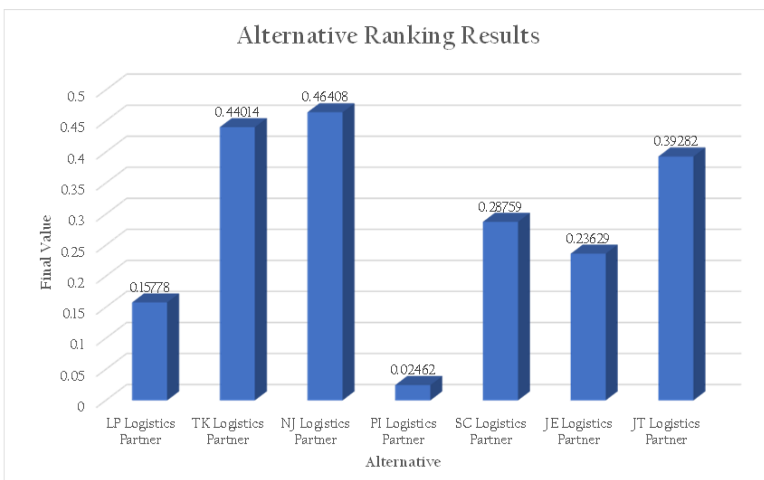

Figure 2. Alternative Ranking

Based on the ranking result graph, NJ Logistics Partner occupies the highest position with a final score of 0.46408, followed by TK Logistics Partner with a score of 0.44014. The third position is held by JT Logistics Partner, which obtained a score of 0.39282, followed by SC Logistics Partner with a score of 0.28759. In the next rank is JE Logistics Partner with a score of 0.23629, while LP Logistics Partner is in the following position with a score of 0.15778. The lowest score

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is obtained by PI Logistics Partner at 0.02462, placing it at the last position in the overall evaluation results.

4.5. Sensitivity Analysis

Sensitivity analysis is conducted to test the extent to which the obtained ranking results remain consistent when there are changes in the criteria weights or small variations in the input data[20]–[22]. Through this approach, each criteria weight is adjusted gradually in certain scenarios to observe its impact on the final value and the ranking positions of the alternatives. The aim is to ensure that the top-ranked alternatives are not easily displaced merely due to small changes in parameters, so that the decision outcomes can be considered stable and reliable. Additionally, this analysis also helps identify which criteria have the most influence on ranking changes, thereby providing a deeper understanding of the decision structure formed[23], [24]. Thus, sensitivity analysis not only serves as a validation stage, but also as an evaluation tool to assess the robustness of the model in facing data uncertainty and variations in weighting assumptions.

Testing changes in criteria weights was carried out by increasing by 0.05 and decreasing by 0.05 for each weight alternately to observe the impact on the ranking structure of alternatives[25]. In the increase scenario, one criterion was raised by 0.05 while the weights of the other criteria were adjusted proportionally to keep the total weight balanced, allowing observation of how an increased level of importance affects the final value and the position of the alternatives. Conversely, in the reduction scenario, the weight of a criterion was lowered by 0.05 and the distribution of the other weights was readjusted to maintain the consistency of the total weighting. This approach allows the identification of criteria that are most sensitive to changes, especially if there is a significant shift in the ranking order. Through this process, it can be determined whether the best alternative remains stable or actually changes when there are small variations in the weighting parameters, so that the robustness of the model can be evaluated comprehensively. The results of the weight changes in both scenarios are presented in Table 10.

Table 10. Scenario Sensitivity Analysis

Alternative	Transit Time	On-Time Delivery	First-Attempt Success	Attempt Rate	Package Volume
Initial Weight	0.2982	0.0028	0.0043	0.0019	0.6929
Scenario 1	0.2505	0.0504	0.0043	0.0019	0.6929
Scenario 2	0.2631	0.0029	0.0545	0.002	0.7276
Scenario 3	0.2505	0.0028	0.0043	0.0495	0.6929
Scenario 4	0.2505	0.0028	0.0043	0.0019	0.7405
Scenario 5	0.2243	0.0031	0.0047	0.0021	0.7658
Scenario 6	0.2769	0.0000	0.0047	0.0021	0.7658
Scenario 7	0.2769	0.0031	0.0000	0.0021	0.7658
Scenario 8	0.2769	0.0031	0.0047	0.0000	0.7658
Scenario 9	0.2769	0.0031	0.0047	0.0021	0.7132
Scenario 10	0.2982	0.0028	0.0043	0.0019	0.6929

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Based on all the simulated weight change scenarios, each subsequent weight composition was used to recalculate preference values and compile the ranking of alternatives for each condition. This process was carried out to observe whether changes in the distribution of criterion importance levels, whether through increases, decreases, or temporary removal of a weight, had a significant impact on the relative positions of each alternative. By comparing the ranking results from Scenario 1 to Scenario 10 against the initial weight conditions, the level of consistency and stability of the model across various weighting configurations can be evaluated. This analysis provides a comprehensive overview of the resilience of decision outcomes to the dynamics of changing criteria priorities, and the ranking results for all these scenarios are displayed in Figure 3.

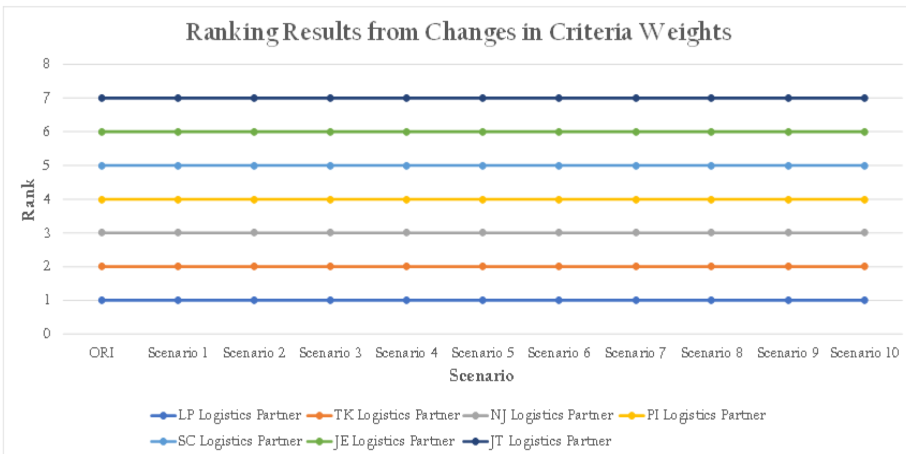

Figure 3. Alternative Rankings from Changes in Criteria Weights

The ranking results chart from changes in criteria weights shows that the position of each alternative remains consistent from the initial condition to Scenario 10 without any ranking shifts. LP Logistics Partner stays stable in the first rank, followed consecutively by TK Logistics Partner in second place and NJ Logistics Partner in third place. PI Logistics Partner remains in fourth place, then SC Logistics Partner in fifth, JE Logistics Partner in sixth, and JT Logistics Partner consistently occupies the seventh rank. The parallel and non-intersecting line patterns across all scenarios confirm that a weight change of 0.05, whether an increase or decrease, does not affect the structure of alternative rankings. This indicates that the model has a very strong level of stability and resilience against variations in criteria weighting.

4.6. Result Analysis and Recommendation

The analysis results show that the weighting structure generated through the MPSI method places very strong emphasis on the Package Volume and Transit Time criteria, while the other criteria contribute relatively little. The dominance of these two criteria directly impacts the

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alternative ranking results, where logistics partners with high volume capacity and more efficient delivery times tend to occupy the top positions. This pattern is consistent in both the initial calculation results and across all sensitivity test scenarios, which show no change in ranking positions even with variations in weights. This stability indicates that the model has a good level of resilience to parameter changes, making the decision results reliable. In addition, ranking consistency also shows that the performance differences between alternatives are significant enough that they are not easily displaced by moderate weight adjustments.

From a managerial interpretation perspective, the alternative in the top position can be considered a priority partner because it is able to meet the main criteria that have the greatest influence in the model. Advantages in package volume and transit time efficiency indicate a more stable operational capacity and better distribution capability compared to other alternatives. Meanwhile, alternatives in the middle ranking still have potential to be improved, particularly in aspects that have dominant weight in order to compete more competitively. For alternatives at the bottom ranking, these results serve as an indicator of the need for a comprehensive evaluation of operational performance and the service strategies implemented. Organizations can use these findings as material for reflection to improve the distribution system, enhance timeliness, or optimize the management of shipment volumes. By understanding which factors most influence the outcomes, the decision-making process becomes more focused and data-driven. This approach helps management prioritize resources on aspects that truly have a significant impact on overall performance.

Based on the overall analysis, it is recommended that the logistics partner evaluation process be conducted periodically by updating performance data so that the decision outcomes remain relevant to the actual conditions. In addition, although the model has been proven stable against changes in weighting, exploring weighting methods or other ranking methods can be done as a comparison to enrich the analytical perspective. The integration of additional, more specific performance indicators can also be considered to make the evaluation more comprehensive and to reflect broader operational dynamics. The implementation of a decision support system based on this method should be complemented with a monitoring dashboard so that management can track performance changes in real time. In this way, strategic decisions are not only reactive but also proactive in facing potential distribution risks. Furthermore, collaboration with selected logistics partners needs to be strengthened through clear and measurable performance agreements. Through these steps, the analysis results do not stop at the evaluation stage but rather become the basis for implementing sustainable and service-quality-oriented policies.

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V. Conclusion

The integration of the MPSI method for criteria weighting and PIV for the ranking process is able to produce decisions that are objective, structured, and consistent in evaluating the performance of logistics partners. The weighting results show that Package Volume and Transit Time are the most influential factors in determining the final position of alternatives, while other criteria contribute less to performance differentiation. The ranking process produces a clear and stable order of alternatives, which is then reinforced through sensitivity tests with various weight change scenarios. The absence of rank shifts in all scenarios indicates that the model has a high level of resilience to parameter variations, making the decision results robust and reliable. Overall, this approach not only provides a quantitative picture of the relative performance of each alternative but also provides a strong basis for data-driven strategic decision-making. Moving forward, research can be developed by adding more diverse criteria such as operational cost aspects, customer satisfaction, or distribution risk levels to make the evaluation more comprehensive. In addition, combining it with other multi-criteria decision-making methods or approaches based on fuzzy logic and machine learning can also be explored to address data uncertainty and improve result accuracy.

Future research can extend this framework by incorporating more diverse and dynamic criteria, including operational costs, customer satisfaction, delivery reliability, service quality, environmental performance, and distribution risk, to provide a more comprehensive evaluation of logistics partners. The analysis can also be expanded using larger datasets and real-time or longitudinal logistics data to examine whether the ranking remains consistent across different periods and operational conditions. In addition, comparative experiments involving other objective weighting and ranking methods can be conducted to further evaluate the methodological performance and generalizability of the proposed approach. The integration of fuzzy, grey, probabilistic, or interval-based approaches may also be explored to accommodate uncertainty and imprecision in logistics evaluation data. Furthermore, machine learning techniques could be incorporated to identify hidden performance patterns, predict logistics partner performance, and support adaptive decision-making. Future studies may also investigate the application of the proposed framework across different logistics sectors, regions, and supply chain structures to assess its transferability and practical applicability. These extensions are expected to strengthen the analytical capability of the framework and provide more comprehensive support for strategic logistics partner selection and management.

CRediT Authorship Contribution Statement

Sufiatul Maryana: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Conceptualization. **Arie Qur’ania:**

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Writing – original draft, Formal analysis, Data curation, Conceptualization. **Agung Prajuhana Putra:** Writing – original draft, Software, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Declaration of Generative AI and AI-assisted Technologies in The Writing Process

The authors used Generative Artificial Intelligence to improve the writing clarity of this paper. They reviewed and edited the AI-assisted content and take full responsibility for the final publication.

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