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The Role of Logistics Industry Orchestration in Mediating Service Quality, Brand Image and Price, Over The Service Ecosystem

Esa Setia Wiguna[1], HM. Thamrin[2], Edhie Budi Setiawan[3], Yana Tatiana[4]
[1]Trisakti Institute of Transportation and Logistics, Jakarta, Indonesia, eswiguna@gmail.com
[2]Trisakti Institute of Transportation and Logistics, Jakarta, Indonesia, thamrin@itltrisakti.ac.id
[3]Trisakti Institute of Transportation and Logistics, Jakarta, Indonesia, edhie.budi@gmail.com
[4]Trisakti Institute of Transportation and Logistics, Jakarta, Indonesia, yana23011972@gmail.com

Corresponding Author: eswiguna@gmail.com[1]

Abstract: A powerful wave of change has swept across the global business landscape over the past seven to eight years. Three fundamental disruptions—digitalization permeating every aspect of life, the dominance of the millennial generation with its unique preferences, and the pandemic that drastically altered the socio-economic order—have significantly reshaped consumer behavior. These conditions have forced the freight forwarding industry in Indonesia to undergo radical transformation: from merely providing product-based services to building an integrated service ecosystem. This crucial transformation aims to optimize overall business performance and enhance the quality of national cargo services. his study delves deeply into how Service Quality, Brand Image, and Price converge to build a robust service ecosystem among Indonesian freight forwarding companies. The goal is to orchestrate various stakeholders within the complex logistics ecosystem. Adopting a quantitative approach, the study develops a model consisting of five construct variables and 50 indicators, all of which have been rigorously tested for validity and reliability. Data was collected using a Likert scale (1–5) questionnaire survey involving company leaders from freight forwarding firms, including members of logistics associations. Using a combination of area proportional random sampling and stratified proportional random sampling, data was successfully collected from 300 respondents. The data analysis was conducted using the Structural Equation Modeling (SEM) method with the SmartPLS software. The results reveal the central role of price in influencing logistics industry orchestration and the formation of a service ecosystem. Competitive and strategically set pricing proves to be a critical catalyst in facilitating effective interactions among companies within the logistics network. Statistically, the dominant factor in this study is the price variable, which has a significant influence on logistics industry orchestration (coefficient 0.534) and the service ecosystem variable (coefficient 0.490). The findings indicate that efficient pricing strategies aligned with the value offered have great potential to enhance coordination, collaboration, and better management among various actors in the logistics industry. Moreover, superior service quality and a strong brand image also play vital roles in improving the effectiveness of orchestration and strengthening the foundation of the service ecosystem. Overall, the study concludes that all 10 proposed hypotheses are significant, affirming the crucial role of integrated logistics industry orchestration in driving operational efficiency and improving company competitiveness. Therefore, the study recommends that freight forwarding companies in Indonesia design smart and adaptive pricing policies, leverage technological advancements and digitalization to optimize operations and cost efficiency, and strengthen strategic partnerships among stakeholders. These steps are essential for realizing a more efficient, sustainable, and competitive logistics ecosystem. The study underscores that effective pricing management is not merely a cost element but a strategic key to enhancing competitiveness and significantly contributing to the creation of a superior and efficient logistics ecosystem.

Keywords: Service Quality, Brand Image, Price, Logistics Industry Orchestration, Service Ecosystem.

INTRODUCTION

The logistics industry has undergone a transformation in its role over the past three decades. It has become a crucial factor in modern logistics planning in today's economy. By expanding its services, it offers value-added products, helping supply chains in industry and retail achieve substantial economies of scale and scope. Markets with well-organized logistics facilities and supply chain management have a distinct advantage over other economies, while improving logistics infrastructure can serve as a competitive and effective tool in increasing market share.(Kherbach & Mocan, 2016). Supply chain integration is considered strategically and operationally important but the role of logistics service providers in supply chain integration remains unclear.(Fabbe-Costes & Roussat, 2011).

In practice, logistics companies can carry out various businesses simultaneously or a combination of businesses in the fields of courier/express/deposit services, transportation, distribution, customs, export-import, normal warehousing, refrigerated warehousing, as well as warehousing that has evolved not only as a place to store goods but also to carry out other activities that are still within the logistics corridor, according to orders from customers.

Logistics industry orchestrationalso plays a crucial role in creating an efficient logistics ecosystem. Effective logistics orchestration includes strong coordination between transportation service providers, warehouses, and other partners. However, in Indonesia, the lack of integration between various transportation modes—such as land, sea, and air—often hinders the efficient distribution of goods. This lack of integration among distribution systems hampers logistics efficiency, resulting in wasted time and resources. As explained by Shen et al. (2024), poor orchestration can lead to delivery delays, wasted resources, and increased operational costs. Therefore, better management of logistics orchestration, including the adoption of technology to accelerate the flow of goods and strengthen connectivity between transportation modes, is crucial to improving efficiency in Indonesia's logistics ecosystem.

Logistics industry orchestration serves as a mediating variable that connects various logistics capabilities and resources to between the capabilities or resources of logistics actors and the achievement of optimal service ecosystem performance. In this case, orchestration encompasses the process of coordinating roles, aligning goals, and integrating the flow of information, goods, and services among various stakeholders—such as freight forwarders, port operators, transportation companies, customs agents, and customers—to create synergies that generate shared value (co-created value). As a mediating variable, orchestration explains how inputs such as technology, regulations, or human resource competencies can be transformed into outputs in the form of increased efficiency, customer satisfaction, and industry competitiveness. In other words, even though supporting factors are in place, without effective orchestration, relationships between actors in the logistics supply chain are often fragmented, thus preventing optimal benefits from being achieved. Conversely, good orchestration can convert this potential into tangible results for the logistics ecosystem as a whole.

Data-driven orchestration and ecosystems, Kolagar (2024) developed a multi-level framework for orchestration in creating sustainable digital solutions, but the application of this framework in the case of Indonesian freight forwarders, which combine digital technology and physical logistics processes, is still very limited. In addition, Shen et al.'s (2024) research on ecosystem orchestration practices for industrial companies suggests the need for a broader orchestration framework, but this has not been directly translated to freight forwarders operating in developing countries such as Indonesia.

Furthermore, while several studies have addressed the relationship between logistics capabilities and innovation in the context of 3PLs (Chirico et al., 2024; Kmiecik & Wierzbicka, 2024), the implementation of logistics innovation in Indonesian freight forwarders remains underexplored. Bian et al.'s (2021) study on the role of 3PLs in the healthcare sector and their impact on shipping efficiency demonstrates the importance of data-driven logistics management, but does not investigate its application in international freight shipments. Another gap is found in the application of collaboration in the supply chain using 3PLs as orchestrators, as described by Pretel & Guitart-Tarrés (2021) and Gitau (2022), but there is less focus on cross-sector collaboration in the context of Indonesia.

Research by Kara & İpekçi (2022) and Rodríguez-Espíndola et al. (2024) on the relationship between logistics capabilities and operational performance indicates that logistics innovation plays a significant role in improving performance, however, the application of this theory to Indonesian freight forwarders integrating innovation into their daily operations, as well as its impact on their operational strategies, still requires further research. In this regard, research by Bukhari et al. (2023) which introduced a quantitative performance management framework (QPMF) to improve the economy through omnichannel integration in the banking and marketing sectors provides a useful perspective for understanding how quantitative performance models can be applied to optimize logistics ecosystem management, however further research is needed to examine its practical application in the freight forwarding sector.

Based on the research explanation above, the main challenge in this study is that orchestration in the logistics industry in Indonesia is crucial and urgently needed to manage the flow and sustainability of the freight forwarder company's service ecosystem. This in turn can increase efficiency, reduce costs, and accelerate delivery durations. This will ultimately improve Indonesia's LPI ranking, which will also have an impact on increasing the competitiveness of freight forwarder companies in Indonesia.

Overall, service quality, brand image, pricing, and logistics industry orchestration are key factors influencing the efficiency of Indonesia's logistics service ecosystem. When these factors are not managed effectively, the impact is seen in declining logistics efficiency, contributing to Indonesia's declining position in the Logistics Performance Index (LPI). To improve Indonesia's position in the LPI, a transformation involving improved service quality, strengthened brand image, reduced logistics costs, and more integrated orchestration is essential. By improving these factors, Indonesia can enhance the competitiveness of its logistics sector and optimize the efficient flow of goods, ultimately enhancing its position in the global market.

However, orchestration in the Indonesian logistics industry has not been optimally implemented. This is due to several factors, including: inequality in service levels and quality between parties within the freight forwarder service ecosystem, which can be an obstacle. Similarly, infrastructure within freight forwarder companies, with limited technology utilization, can be a barrier to creating efficient orchestration. Another issue is mismatch, with the large number of parties involved, from producers and distributors to freight forwarder service providers, leading to a lack of coordination and collaboration. Orchestration requires integration and synergy between elements within the ecosystem, which is often difficult to achieve due to fragmentation and system inconsistencies. Another challenge is that some parties within the freight forwarder service ecosystem are not yet fully aware of the benefits of logistics orchestration, which can provide added value and competitive advantage.

METHOD

The research stages in this study begin with a pre-research survey, which involves observing, seeing, and listening to all phenomena in the field. It reviews literature studies related to the use of relevant theories in determining grand theory, middle theory, and variable theory. It then continues with a review of previous research findings. The first stage is identifying a relevant and interesting research topic. This research topic relates to the field of service marketing management and has the potential to contribute to the development of the logistics industry service ecosystem. Once the research topic has been identified, the next step is to formulate a clear and focused research problem. This problem addresses challenges that remain unresolved in the field of service marketing management. This research problem formulation is specific, focused, and can be answered through a systematic research method.

The population in this study were the top leaders of Freight Forwarder companies that are members of ALFI (Indonesian Logistics and Forwarders Association), spread across 34 DPW (Regional Leadership Councils) in the Greater Jakarta area. The total number of ALFI member companies in the Greater Jakarta area is recorded at around 1,300 companies, which are divided equally among the 34 DPWs, with each DPW managing around 38 companies. (ALFI, 2023) Thus, each DPW has a company population that ranges from that number, and all companies registered in the 34 DPWs in Greater Jakarta are the relevant subjects in this study. This population includes companies engaged in logistics and forwarding that are registered as ALFI members in the region.

However, although Hair's formula suggests a minimum sample size of 100, the researchers decided to sample 300 freight forwarding companies. This decision was made to increase the accuracy and reliability of the research results, taking into account the potential for greater variability in the data and to ensure a broader representation of the population studied. By selecting a larger sample, the researchers hoped to increase the statistical power of the study, reduce the margin of error, and obtain results that were more representative and generalizable to a larger population, namely all ALFI member companies registered in the Greater Jakarta area.

This research is quantitative and uses a survey approach, where inferential analysis is conducted using relevant statistical methods. Because the conceptual framework or research model is highly complex with various latent variables or constructs, we chose to use multivariate analysis. This approach was chosen because it is appropriate for the complexity of the research, which involves many latent variables or constructs.(Sekaran & Bougie, 2020) (Sarstedt et al., 2021).

Data analysis aims to present all data into smaller components in order to identify the dominant components, comparisons between components, and comparisons of components with all components.(Sugiyono, 2019a)Data analysis techniques are useful for answering research questions or testing hypotheses that researchers have formulated. The data management in this study will utilize SMARTPLS software.

Structural equation modeling(SEM) is a procedure used to address the shortcomings of regression methods. Methodologists divide structural equation modeling (SEM) into two approaches: covariance-based SEM (CBSEM) and variance-based SEM, or partial least squares (PLS). PLS is a powerful analytical procedure because it does not rely on a number of assumptions. PLS is distribution-free, meaning its modeling does not require data with a normal distribution.(Waluyo, 2016).

RESULTS AND DISCUSSION

Respondent Characteristics

From the questionnaire distribution, 300 respondents met the specified criteria. A description of the respondent profiles, which served as the source of the research data analysis, is presented in the table. The analysis begins with respondent profile data, followed by descriptive analysis and hypothesis testing conducted on all sampled respondents, followed by a discussion of the results of the PLS 4.0.9.6 model analysis.

1. Respondent Demographic Profile

Table 4.1. Gender

No	Gender	f	%
1	Man	169	56.3
2	Woman	131	43.7
Total		300	100.0

Source: Processed primary data (2025)

The table above illustrates the respondent data by gender. The table shows that the majority of respondents were male, at 56.3%, or 169 people.

Table 4.2. Age

No	Age	f	%
1	30-45 years	92	30.7
2	46-60 years	120	40.0
3	Over 60 years old	88	29.3
Total		300	100.0

Source: Processed primary data (2025)

The table above illustrates the respondent data by age. The table shows that 40.0% of the respondents, or 120 people, were aged between 46 and 60 years old.

Table 4.3. Position

No.	Position	f	%
1	Company owner	156	52.0
2	Company Leader/Director	144	48.0
Total		300	100.0

Source: Processed primary data (2025)

The table above illustrates the respondent data by job title. The table shows that 52.0%, or 156 people, are business owners.

Table 4.5 Company Categories

No	Company Category	f	%
1	Multinational	133	44.3
2	National	167	55.7
Total		300	100.0

Source: Processed primary data (2025)

The table above illustrates the respondent data by company category. The table shows that the majority of respondents own national companies, accounting for 55.7%, or 167 individuals.

Statistical Analysis

The results of data processing with the PLS Algorithm produce an outer model image as shown below.

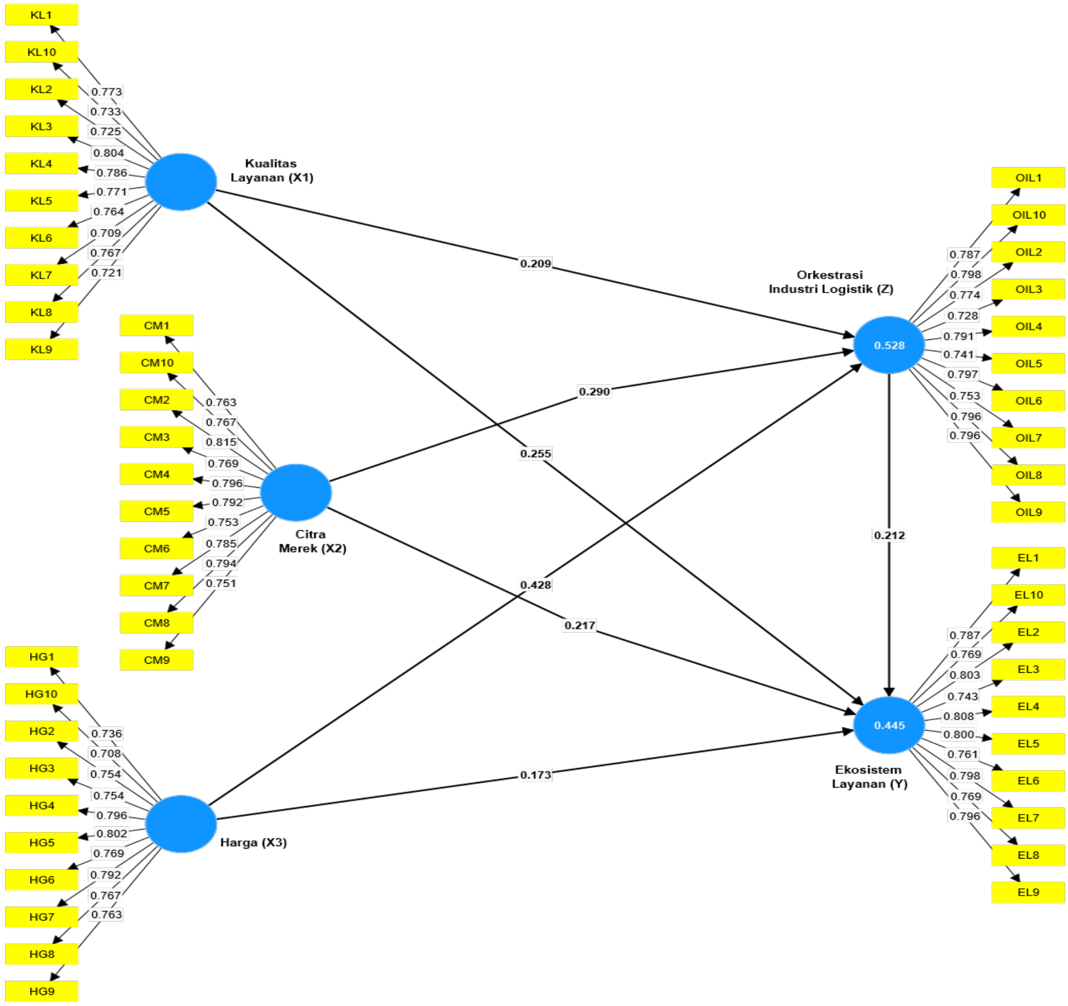

Figure 4.1 Outer model results
Source: Results of PLS-SEM research data processing (2025)

The outer model results yielded 40 reflective indicators used in the research model. Figure 4.2 above demonstrates that all 40 indicators reliably measured their constructs, meeting the required outer loading values (Hair et al., 2019). The following provides a detailed explanation of the outer model evaluation results.

Indicator Validity

The first step in outer loading analysis is to assess indicator reliability. Data processing using PLS-SEM yields an outer loading value, indicating the relationship between the indicator and its construct. There are required values as thresholds for each indicator to be considered reliable in measuring its construct. In PLS-SEM, an indicator is considered reliable if its outer loading value is greater than 0.70.

Table 4.14 Outer Loading Values

Variables	Indicator	Outer Loading	Information
Service Quality (X1)	KL1	0.773	Valid
	KL2	0.725	Valid
	KL3	0.804	Valid
	KL4	0.786	Valid
	KL5	0.771	Valid
	KL6	0.764	Valid
	KL7	0.709	Valid
	KL8	0.767	Valid
	KL9	0.721	Valid
	KL10	0.733	Valid
Brand Image (X2)	CM1	0.763	Valid
	CM2	0.815	Valid
	CM3	0.769	Valid
	CM4	0.796	Valid
	CM5	0.792	Valid
	CM6	0.753	Valid
	CM7	0.785	Valid
	CM8	0.794	Valid
	CM9	0.751	Valid
	CM10	0.767	Valid
Price (X3)	HG1	0.736	Valid
	HG2	0.754	Valid
	HG3	0.754	Valid
	HG4	0.796	Valid
	HG5	0.802	Valid
	HG6	0.769	Valid
	HG7	0.792	Valid
	HG8	0.767	Valid
	HG9	0.763	Valid
	HG10	0.708	Valid
Service Ecosystem (Y)	EL1	0.787	Valid
	EL2	0.803	Valid
	EL3	0.743	Valid
	EL4	0.808	Valid
	EL5	0.800	Valid
	EL6	0.761	Valid
	EL7	0.798	Valid
	EL8	0.769	Valid
	EL9	0.796	Valid
	EL10	0.769	Valid
Logistics Industry Orchestration (Z)	OIL1	0.787	Valid
	OIL2	0.774	Valid
	OIL3	0.728	Valid
	OIL4	0.791	Valid

Variables	Indicator	Outer Loading	Information
	OIL5	0.741	Valid
	OIL6	0.797	Valid
	OIL7	0.753	Valid
	OIL8	0.796	Valid
	OIL9	0.796	Valid
	OIL10	0.798	Valid

Source: Results of PLS-SEM research data processing (2025)

Based on the outer loading model data from Table 4.14, it can be concluded that all indicators in this research model are reliable for measuring their respective constructs.

Construct reliability

The second stage in the outer loading analysis is to assess construct reliability. This value is needed to determine the internal consistency of respondents' answers to the indicator items of a construct. From the PLS-SEM data processing results, construct reliability values are obtained to assess the extent to which the construct can be reliably measured by its indicators. In this outer model analysis, reliability testing is carried out by evaluating Cronbach's alpha and Composite Reliability values (Hair et al., 2019; Hair et al., 2020). The required limit value as a reference is a Cronbach's alpha value above 0.6 as the lower bound, while the Composite Reliability value is expected to be between 0.7 and 0.95. A Composite Reliability value of 0.95 is considered the upper bound; therefore, if it is found to be greater than this value, it can be suspected that there is redundancy in the use of indicators (Hair et al., 2019).

Table 4.15 Cronbach Alpha and Composite Reliability Values

Variables	Cronbach's alpha	Composite reliability	Cut-off Value	Results
Service Quality (X1)	0.916	0.919	>0.70	Reliable
Brand Image (X2)	0.928	0.929		Reliable
Price (X3)	0.921	0.923		Reliable
Logistics Industry Orchestration (Z)	0.927	0.928		Reliable
Service Ecosystem (Y)	0.930	0.932		Reliable

Source: Results of PLS-SEM research data processing (2025)

Table 4.13 above shows that the Cronbach's alpha values for all variables are above 0.6, as required. Furthermore, all variables have Composite Reliability values above 0.7. Therefore, the measurement model can be considered reliable, meaning all indicators are confirmed to be reliable and consistently measure their respective constructs.

1) Construct Validity

The third stage in outer loading analysis, after testing reliability, is to assess construct validity, or in the reflective model, convergent validity. The reference value used as the lower acceptable limit is the average variance extracted (AVE) of a construct's indicators. A latent variable or construct is considered valid if its AVE is greater than 0.50 (Hair et al., 2019; Hair et al., 2020).

Table 4.16 Average variance extracted (AVE) value

Variables	Average variance extracted (AVE)	Results
Service Quality (X1)	0.571	Valid
Brand Image (X2)	0.606	Valid
Price (X3)	0.585	Valid
Logistics Industry Orchestration (Z)	0.603	Valid
Service Ecosystem (Y)	0.614	Valid

Source: Results of PLS-SEM research data processing (2025)

Table 4.16 above shows the average variance extracted (AVE) value for each variable, with all research variables in this research model exceeding the required 0.50. Based on this, it can be concluded that the indicators in this research model are considered valid for collectively measuring their respective constructs.

An assessment has been conducted on four statistical parameters resulting from the reliability and validity tests on the outer model as above, namely indicator reliability (outer loading), construct reliability (Cronbach's alpha and Composite Reliability), construct validity (average variance extracted or AVE). Based on the outer PLS-SEM model data, a statistical conclusion can be drawn, namely that in this research model all indicators have been declared reliable and valid to measure each construct specifically. Thus, it is worthy to continue to the next stage of analysis, namely the inner model test (structural model).

Inner Model Results (Structural Model)

In the data analysis stage using PLS-SEM, after evaluating the outer model, the next step is to assess the inner model, or structural model. At this stage, a one-tailed hypothesis test is conducted using the resampling method with bootstrapping using SmartPLS4 software. Bootstrapping is a non-parametric procedure that uses resampling techniques to test the significance and coefficients of SmartPLS4 (Ringle et al., 2015; Memon et al., 2021). The test data from the inner model are used to assess the relationships between latent variables (constructs) in a research model.

In accordance with the instructions from Hair et al. (2019), before reporting the hypothesis testing, the inner model test output needs to first examine the quality of the research model proposed for empirical testing. Model quality parameters used in the inner model are Variance Inflation Factor (VIF), R-square, f-square, Q-square, Q-square Predict (Hair et al., 2019; Hair et al., 2021). This model quality is used to assess the explanatory and predictive capabilities of the proposed research model in accordance with the considerations of using PLS-SEM. Afterward, a significance test is conducted to determine whether the hypothesis can be supported and a path analysis is performed through the results of the specific indirect effects test. Finally, an importance-performance mapping analysis is added based on IPMA data that uses the total effect value on the target construct and the mean data from the respondents' answers (Ringle & Sarstedt, 2016). The importance-performance mapping analysis (IPMA) analysis can provide input for managers in setting priorities (Hair et al., 2019). Below are the results of the inner model image from the PLS-SEM bootstrapping results along with a description:

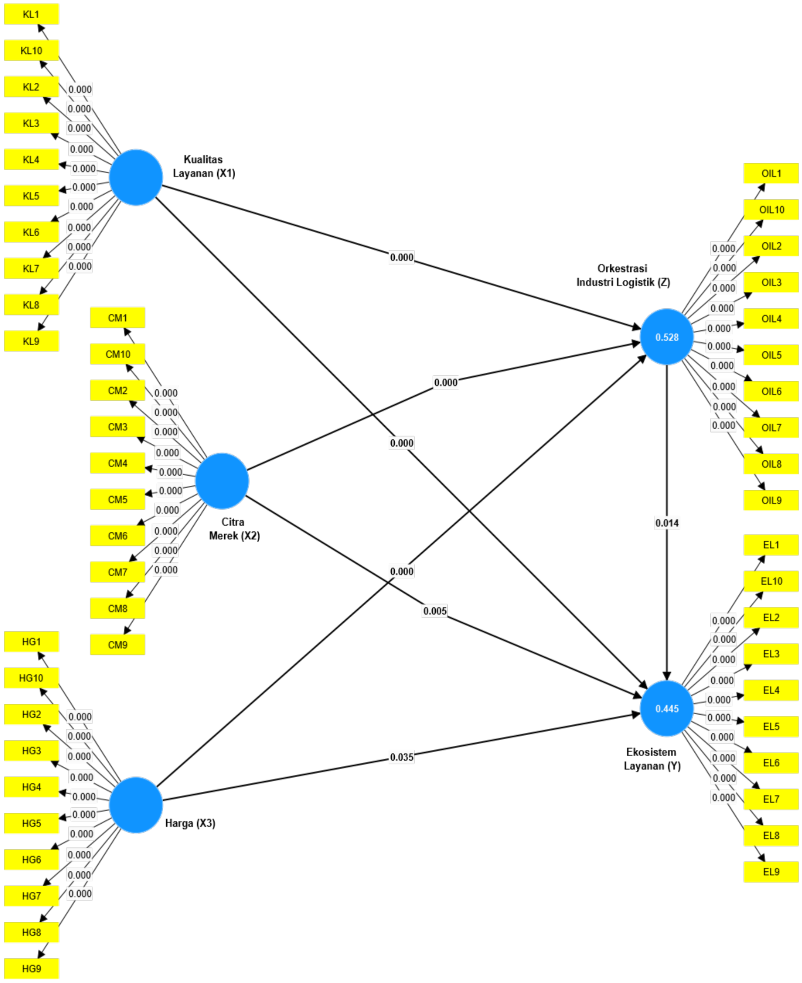

Figure 4.2 Inner Model Results

Source: Results of PLS-SEM research data processing (2025)

The bootstrapping results, in the form of the inner model image above, demonstrate the structural relationships between variables in this research model. This model contains one dependent variable, three independent variables, and one mediating variable. The inner model image shows the T-statistic values for the 10 paths in the research model. All paths in the research model have T-statistic values above the T-table, thus concluding that all paths in the structural model are significant.

The detailed explanation of the inner model test results is written sequentially according to the reporting stages recommended by Hair et al. (2019).

Multicollinearity

In structural model analysis, the first step reported is to evaluate the presence or absence of collinearity issues or problems between independent variables. Multicollinearity is a situation where there is a strong correlation or relationship between two or more independent variables in a model. Models with large multicollinearity have large standard errors and therefore reduce the model's precision capability. In PLS-SEM, the Inner Variance Inflation Factor (VIF) value is used for multicollinearity testing, where the ideal value, or can be said to be no problem found, is if it is less than 3. If the VIF value is more than 5, it can be considered 'critical' or there is already a multicollinearity issue in the research model that will affect the value of the path coefficient in the research model (Hair et al., 2019). If the VIF value is found between 3-5, it can be said that there is a suggested value in the multicollinearity test or is still within tolerable or acceptable limits.

Table 4.17 Inner VIF Value

	Service Ecosystem (Y)	Logistics Industry Orchestration (Z)
Brand Image (X2)	1,554	1,375
Price (X3)	1,653	1,266
Service Quality (X1)	1,360	1,268
Logistics Industry Orchestration (Z)	2,120	

Source: Results of PLS-SEM research data processing (2025)

Table 4.17 above shows the Variance Inflation Factor (VIF) values in the research model test results, where the VIF values for all variables were found to be less than 5. Therefore, it can be interpreted that all variables in the research model have ideal inner VIF values. Based on this, it can be said that there are no multicollinearity issues found among the variables in this research model. This indicates that the quality of this research model is acceptable in terms of not having multicollinearity issues.

1) Coefficient of Determinant (R-Squared)

The second step in the inner model analysis stage is to assess the quality of the research model by looking at the R-square value. The R-squared value or coefficient of determination can be seen from two aspects, the first is explanatory power or how capable the independent variables in the research model can explain the dependent variable. The second is predictive accuracy or how accurately the independent variables in the research model are able to predict the dependent variable to a certain degree, which is measured from weak to strong (Hair et al., 2019). The R-squared value can be called substantial or strong if the value is equal to or greater than 0.75. The R-squared value is said to be moderate to strong if the value is equal to 0.50 - 0.75. The R-squared value is weak if the value is equal to 0.25 - 0.50. However, if the R-square value is found above 0.9, the model can be considered overfit (Hair et al., 2019).

Table 4.18 R-Squared Value

Variables	R-square
Logistics Industry Orchestration (Z)	0.528
Service Ecosystem (Y)	0.445

Source: Results of PLS-SEM research data processing (2025)

Table 4.18 above shows that in substructure 1, the R2 (R-Squared) value for the logistics industry orchestration variable is 0.528, and is therefore classified as having a fairly strong effect. It can be said that the variables of service quality, brand image, and price influence the logistics industry orchestration by 52.8%, while the remaining 47.2% can be explained by other variables not examined.

In substructure 2, the R2 (R-Squared) value for the service ecosystem variable is 0.445, thus categorizing it as being quite strong. It can be said that the variables of service quality, brand image, price, and logistics industry orchestration influence the service ecosystem by 44.5%, while the remaining 55.5% can be explained by other variables not examined.

Effect Size (f-Squared)

In structural model analysis, the next step as a reference for assessing the predictive ability of the suggested model is to look at the f2 (f-Squared) value from the results of PLS-SEM bootstrapping data processing (Hair et al., 2020). The f2 test is used to determine the effect size or magnitude of influence of a construct if there is a change in the R-Squared value of a target construct, when a certain construct as a predictor is omitted from the research model. The f-Squared test provides a value of how large the effect size or effect size is used to evaluate the substantial impact of the predictor variable in the research model. The size of the f-Squared or effect size according to Cohen (1988) is if 0.02 is said to have a small effect size of a latent variable, if 0.15 is said to be a medium effect size of the latent variable, while if more than 0.35 is said to have a large effect size of a latent variable. The value of 0.02 itself is considered to be the significant limit of the effect that can be given by a latent variable, if f2 is found to be lower than 0.02 then it is said that it does not have a large enough effect size to provide a meaningful influence (Cohen, 1988). From the bootstrapping process, the f2 value in this research model is obtained as follows;

Table 4.19 f-Squared Values

Influence	Effect Size Value	Information
Brand Image (X2) -> Service Ecosystem (Y)	0.055	Little Influence
Brand Image (X2) -> Logistics Industry Orchestration (Z)	0.130	Little Influence
Price (X3) -> Service Ecosystem (Y)	0.033	Little Influence
Price (X3) -> Logistics Industry Orchestration (Z)	0.306	Moderate Influence
Service Quality (X1) -> Service Ecosystem (Y)	0.086	Little Influence
Service Quality (X1) -> Logistics Industry Orchestration (Z)	0.073	Little Influence
Logistics Industry Orchestration (Z) -> Service Ecosystem (Y)	0.038	Little Influence

Source: Results of PLS-SEM research data processing (2025)

Table 4.18 above shows that the price variable has the greatest influence on the orchestration of the logistics industry, with an effect size of 0.306. Therefore, it can be said that price has a significant impact on the orchestration of the logistics industry, making this variable an important predictor in predicting the orchestration of the logistics industry.

Predictive relevance values (Q2 and Q2_Predict)

In analyzing model quality in PLS-SEM, the next step is through the Q-Squared test. This test aims to determine the predictive relevance of a latent variable in the research model (Hair & Sarstedt, 2021). The Q2 value is in the range of 0 to 1 (Hair et al., 2019). If the Q-Squared value is found to be greater than 0, it is said to have relevance. If the value is up to 0.25, it is said to have small predictive relevance. If the Q-Squared value is between 0.25 and 0.5, it is said to have medium predictive relevance. If the Q-Squared value is more than 0.5, it is said to have large predictive relevance. The higher the Q-Squared value found or the closer it is to 1, the more accurate the predictive ability of a research model to predict relatively similar research outputs when there are changes in data parameters. This is done in PLS-SEM using an out-of-sample approach, or by simulating changes in the data compared to the original estimated data (Hair et al., 2019; Hair & Sarstedt, 2021). Therefore, it can be said that this value can indicate the quality of the proposed model for empirical testing, considering that this model will be tested on different data sets in the future.

A more advanced statistical method for testing Q-Squared values has been used in PLS-SEM analysis through the PLS_Predict calculation. This method was developed and published by Shmueli et al. (2018) and is currently considered more accurate than blindfolding (Hair et al., 2019; Hair & Sarstedt, 2021). The predictive ability of the PLS_Predict calculation is considered more sensitive to changes in input data parameters. This test is useful in providing information regarding the potential relevance between latent variables in the study. Q2 Predict values can also be grouped into three groups:

small predictive relevance : < 0.25
medium Predictive relevance : 0.25 – 0.5
large predictive relevance : > 0.5

The Q2 value of this study was obtained from the calculation results using the blindfolding menu in PLS-SEM as shown in the table below.

Table 4.20 Q-Square Test (Q2) or Predictive Relevance

Variables	Q^2Predict	Results
Logistics Industry Orchestration (Z)	0.506	*large predictive relevance*
Service Ecosystem (Y)	0.388	*medium*Predictive relevance

Source: PLS-SEM data processing results (2025)

Table 4.20 shows that the Logistics Industry Orchestration variable (Z) is 0.506 and the Service Ecosystem variable (Y) is 0.388. With these results, it can be concluded that every change that occurs in the (exogenous) variables, namely Service Quality (X1), Brand Image (X2) and Price (X3) can predict every change in the Logistics Industry Orchestration variable (Z) relatively strongly and every change in the Service Ecosystem variable (Y) relatively moderately.

***Cross-Validated Predictive Ability Test Results*(CVPAT)**

Cross-Validated Predictive Ability Test (CVPAT) analysis to compare the performance of the Partial Least Squares Structural Equation Modeling (PLS-SEM) method with the Indicator Average (IA) approach. The purpose of this analysis is to evaluate the predictive superiority of both methods in measuring the financial performance of passenger shipping companies. From the results of data processing with smartPLS version 4 software, the results obtained are as per Table 4.21 as follows:

Table 4.21 Cross-Validated Predictive Ability Test (CVPAT)

	ALD	*T Statistics*	*P value*	Information
Service Ecosystem (Y)	-0.921	6,580	0.000	Significant
Logistics Industry Orchestration (Z)	-0.912	6,872	0.000	Significant
Overall	-0.916	7,234	0.000	Significant

Source: PLS-SEM data processing results (2025)

Based on table 4.21, the following results were obtained:

1. In the Logistics Industry Orchestration variable (Z), the analysis results show that the average loss difference (ALD) between the PLS-SEM and IA methods is -0.921, with a t-value of 6.580 and a p-value of 0.000. This indicates that the PLS-SEM method has a significant predictive advantage over IA in modeling Logistics Industry Orchestration.
2. In the Service Ecosystem variable (Y), the analysis results show that the average loss difference (ALD) between the PLS-SEM and IA methods is -0.912, with a t-value of 6.872 and a p-value of 0.000. This indicates that the PLS-SEM method has a significant predictive advantage over IA in modeling the Service Ecosystem.

3. Overall, the analysis results show that the average loss difference (ALD) between the PLS-SEM and IA methods is -0.916, with a t-value of 7.234 and a p-value of 0.000. These results indicate a significant overall superiority of the PLS-SEM method compared to IA in modeling the relationship between research variables.
4. Based on the CVPAT test results, the PLS-SEM method was shown to have significant predictive advantages over the IA method for all variables tested in this study. These results support the validity of the research model and provide strong justification for using the PLS-SEM method to evaluate the relationships between the complex latent variables in this study.

Research Hypothesis Test Results

The most important step in analyzing the inner model or structural model in this study is examining the significance values and coefficients of the relationships between variables in the research model. At this stage, the values that are the focus for answering the research questions are identified and interpreted. The first step is to examine the significance of the eight paths in the research model. This significance test aims to determine the significant influence between variables in the research model so that it can be generalized to the population level. This test was conducted using the bootstrapping method with re-sampling and processed with SmartPLS4 (Ringle et al., 2015; Memon et al., 2021).

The results of testing whether a hypothesis can be supported are carried out by assessing the results of empirical tests, namely the significance and coefficient value. The direction of the coefficient must be in accordance with the direction of the previously proposed hypothesis, because the nature of this hypothesis is directional. Because the direction of influence has been stated in the hypothesis, a two-tailed statistical test is performed. If the T-statistic value resulting from bootstrapping is greater than the T-table value, which is 1.96 (with a significance level or alpha of 0.05), then the relationship between variables can be declared significant (Ringle et al., 2015; Sarstedt et al., 2017). The analysis of this research model was conducted using one-tailed bootstrapping with a significance level of 0.05. First, the significance of all paths is observed, then the size of the coefficient (standardized coefficient) on each path is assessed and compared. If the test results have met both requirements, the research hypothesis can be declared supported. The table below shows the results of PLS-SEM data processing to determine the results of the hypothesis test.

Table 4.22 Hypothesis Test Results

Hypothesis	Path	Original sample (O)	T statistics (|O/STDEV|)	P values	Information
Direct Influence					
H1	Service Quality (X1) -> Logistics Industry Orchestration (Z)	0.209	3,777	0.000	Supported
H2	Brand Image (X2) -> Logistics Industry Orchestration (Z)	0.290	4,424	0.000	Supported
H3	Price (X3) -> Logistics Industry Orchestration (Z)	0.428	7,013	0.000	Supported
H4	Service Quality (X1) -> Service Ecosystem (Y)	0.255	3,555	0.000	Supported

Hypothesis	Path	Original sample (O)	T statistics (|O/STDEV|)	P values	Information
H5	Brand Image (X2) -> Service Ecosystem (Y)	0.217	2,801	0.005	Supported
H6	Price (X3) -> Service Ecosystem (Y)	0.173	2.112	0.035	Supported
H7	Logistics Industry Orchestration (Z) -> Service Ecosystem (Y)	0.212	2,463	0.014	Supported
Indirect Influence					
H8	Service Quality (X1) -> Logistics Industry Orchestration (Z) -> Service Ecosystem (Y)	0.044	2,049	0.040	Supported
H9	Brand Image (X2) -> Logistics Industry Orchestration (Z) -> Service Ecosystem (Y)	0.062	2,234	0.026	Supported
H10	Price (X3) -> Logistics Industry Orchestration (Z) -> Service Ecosystem (Y)	0.091	2,250	0.024	Supported

Source: Results of PLS-SEM research data processing (2025)

CONCLUSION

This research offers significant innovations in the development of the logistics industry in Indonesia, particularly for freight forwarders. One of the main contributions of this research is its emphasis on the role of logistics industry orchestration as a mediator connecting various variables such as service quality, brand image, and price with the overall service ecosystem. Previously, many studies focused on individual factors in logistics, but this study combines these three factors into a more comprehensive orchestration model, which can influence the management of goods and information flows more efficiently. Thus, this research provides new insights into how logistics orchestration can strengthen the service ecosystem and increase company competitiveness in the global industry.

Furthermore, this research demonstrates that orchestration in the logistics industry is not merely about managing the flow of goods and information, but also about improving service quality and strengthening brand image. The concept of effective orchestration enables better collaboration between various parties in the logistics ecosystem, which may not have previously been fully integrated. In this regard, the novelty of this research lies in the understanding that orchestration is a key element in creating an efficient and responsive ecosystem to customer needs.

This study also identifies the critical role of pricing in enhancing orchestration in the logistics industry, which directly impacts the effectiveness of the service ecosystem. While pricing was often viewed as a separate variable, this study reveals that competitive and transparent pricing plays a crucial role in enhancing collaboration between stakeholders in the logistics ecosystem. Therefore, freight forwarders need to address pricing aspects that not only benefit customers but also strengthen collaborative networks between partners in the logistics industry.

Another innovation is the application of technology in logistics orchestration, which opens up opportunities for digitalization and automation to increase efficiency. This research provides insights into how freight forwarders can utilize digital-based logistics management systems to optimize coordination and communication within the service ecosystem. This technological innovation represents a significant breakthrough, given the challenges faced by the Indonesian logistics industry, such as limited infrastructure and regulatory complexity. This research also provides guidance for government policy in encouraging public-private sector collaboration to strengthen a more efficient and integrated logistics ecosystem.

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