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Analysis of Cost Efficiency, Travel Time, Characteristics of Goods and Load Capacity on The Selection of Transportation Modes Through Route Optimization as a Mediating Variable

Christin M[1], Maniah[2], Erna Mulyati[3]
[1]Universitas Logistik dan Bisnis Internasional, Bandung, Indonesia, christinmeiliani056@gmail.com
[2]Universitas Logistik dan Bisnis Internasional, Bandung, Indonesia, maniah@ulbi.ac.id
[3]Universitas Logistik dan Bisnis Internasional, Bandung, Indonesia, ernamulyati@ulbi.ac.id

Corresponding Author: christinmeiliani056@gmail.com[1]

Abstract: Transportation mode selection is a strategic decision that affects the operational efficiency of logistics companies. PT Pos Indonesia Regional III Bandung 40004 faces challenges related to low vehicle capacity utilization, high distribution costs, and suboptimal route planning. This study aims to analyze the effects of cost efficiency, travel time, shipment characteristics, and load capacity on transportation mode selection through route optimization as a mediating variable. A quantitative explanatory approach was employed by distributing questionnaires to employees involved in distribution activities, and the data were analyzed using Structural Equation Modeling–Partial Least Squares. The results indicate that cost efficiency, travel time, shipment characteristics, and load capacity have positive and significant effects on route optimization. Route optimization also has a positive and significant effect on transportation mode selection ($T = 5.471$; $p < 0.001$), while the model explains **79.7%** of the variance in transportation mode selection ($R^2 = 0.797$). Furthermore, route optimization significantly mediates the relationships between the operational factors and transportation mode selection. These findings highlight the importance of effective route planning in improving transportation mode selection and logistics performance.

Keyword: Cost Efficiency, Transit Time, Shipment Characteristics, Load Capacity, Route Optimization, Transportation Mode Selection.

INTRODUCTION

The development of the global logistics system driven by increasing international trade, the growth of *e-commerce*, and digital transformation has caused goods distribution activities to become increasingly complex. In modern logistics systems, transportation is a key component that determines operational efficiency as it accounts for the largest proportion of total logistics costs. Therefore, companies are required to be able to manage transportation costs, delivery times, vehicle capacity, characteristics of goods, and the selection of transportation modes in an integrated manner so that the distribution process takes place effectively and efficiently (Christopher, 2016; Rodrigue, 2022).

In Indonesia, these challenges are even greater because of the geographical characteristics of an archipelagic country which causes logistics costs to be relatively high compared to ASEAN countries. The high cost of distribution is influenced by low transportation efficiency, an imbalance in the flow of goods, and the lack of optimal selection of transportation modes and distribution route planning (Bappenas, 2023). This condition requires logistics companies to be able to make appropriate transportation decisions in order to reduce costs while maintaining service quality.

PT Pos Indonesia Regional III Bandung 40004 is one of the national logistics companies that faces these challenges. Based on operational data in 2025, the company still has an average vehicle *load factor* of 25% with a *minimum charge gap* of 59%. In addition, the *Service Window Performance* (SWP) achievement of 92.7% is still below the logistics industry standard of 95%. On the other hand, the diverse characteristics of goods in terms of weight, volume, economic value, and level of urgency cause the need for transportation modes to become increasingly complex. These conditions show that cost efficiency, travel time, characteristics of goods, load capacity, and route optimization are interrelated factors in determining the decision to choose a mode of transportation.

Theoretically, cost efficiency describes the ability of a company to minimize distribution costs without reducing the quality of service (Christopher, 2016). Travel time is the main indicator that determines the speed and reliability of the transportation system (Rodrigue, 2022). The characteristics of goods affect the capacity requirements of the vehicle and the type of mode of transportation used (de Jong et al., 2021), while the load capacity is related to the level of vehicle utilization which affects operational efficiency (Stanković et al., 2023). All of these factors are then integrated through route optimization aimed at determining the most efficient distribution channel by considering the cost, time, distance, and capacity of the vehicle (Toth & Vigo, 2014). The results of route optimization are then the basis for determining the mode of transportation that best suits the company's operational needs (Rodrigue, 2022).

Various previous studies have shown that cost efficiency, travel time, characteristics of goods, load capacity, and route optimization are factors that affect the choice of transportation modes. Patil et al. (2023) state that cost efficiency is a major factor in the decision to choose a mode of transportation. Masudin et al. (2022) found that punctuality affects the quality of logistics services, while Stanković et al. (2023) showed that optimizing vehicle capacity can improve distribution efficiency. Yakovlev et al.'s (2022) research also proves that route optimization is able to reduce mileage and distribution costs. However, most of these studies still test the relationship between variables partially and focus more on direct influences. The role of route optimization as a mediating variable that explains the relationship between cost efficiency, travel time, characteristics of goods, load capacity, and the selection of transportation modes is still relatively limited, especially in state-owned logistics companies.

Based on the background, theoretical studies, and research gaps that have been described, this study aims to analyze the influence of cost efficiency, travel time, characteristics of goods, and load capacity on the selection of transportation modes, as well as analyze the role of route optimization as a mediating variable in this relationship at PT Pos Indonesia Regional III Bandung 40004. The results of this study are expected to contribute to the development of logistics and transportation management studies, as well as become a basis for consideration for companies in increasing the effectiveness of decision-making in choosing transportation modes.

Hypothesis Development

Cost efficiency is one of the main indicators in improving distribution performance. Christopher (2016) explained that transportation cost control can be done through increasing vehicle utilization, reducing mileage, and making more efficient routes. Patil et al. (2023) also prove that cost efficiency influences transportation decisions. Thus, the higher the cost efficiency, the greater the opportunity for the company to optimize routes and choose a more appropriate mode of transportation.

H1: Cost efficiency has a positive effect on route optimization.

H6: Cost efficiency has a positive effect on the choice of transportation mode.

Travel time is an important indicator in determining the effectiveness of distribution. Rodrigue (2022) stated that shorter and more reliable travel times will improve the efficiency of the transportation network. Masudin et al. (2022) also showed that punctuality is an important factor in improving the quality of logistics services. Therefore, travel time is estimated to affect route optimization and decision to choose a mode of transportation.

H2: Travel time has a positive effect on route optimization.

H7: Travel time has a positive effect on the choice of transportation mode.

The characteristics of the goods which include weight, volume, economic value, and level of urgency determine the needs of different distribution handlers. Rodrigue (2022) and de Jong et al. (2021) explain that the characteristics of goods are one of the main determinants in the selection of modes of transportation. Therefore, the characteristics of goods are expected to influence the process of route optimization and the selection of transportation modes.

H3: The characteristics of goods have a positive effect on route optimization.

H8: The characteristics of the goods have a positive effect on the selection of transportation modes.

Optimal load capacity can increase vehicle utilization so that distribution costs become more efficient. Stanković et al. (2023) state that increased vehicle capacity utilization contributes to increased distribution efficiency. Therefore, load capacity is estimated to affect route optimization and transportation mode selection.

H4: Payload capacity has a positive effect on route optimization.

H9: Load capacity has a positive effect on the choice of transportation mode.

Route optimization is the process of determining the most efficient distribution channel based on cost, time, and vehicle capacity. Toth and Vigo (2014) explained that route optimization is able to minimize distribution costs, while Rodrigue (2022) states that the results of route optimization are the basis for determining the most suitable mode of transportation. Thus, the better the route optimization, the more appropriate the decision to choose the mode of transportation.

H5: Route optimization has a positive effect on the choice of transportation mode.

Route optimization is also expected to be a mechanism that explains how operational factors translate into decisions on the selection of transportation modes. Cost efficiency, travel time, characteristics of goods, and load capacity will affect the preparation of distribution routes first before finally determining the mode of transportation used. Therefore, the following mediation hypothesis is proposed.

H10: Route optimization mediates the influence of cost efficiency on the selection of transportation modes.

H11: Route optimization mediates the influence of travel time on the choice of transportation mode.

H12: Route optimization mediates the influence of goods characteristics on the selection of transportation modes.

H13: Route optimization mediates the influence of load capacity on the selection of transportation modes.

Based on theoretical studies, previous research, and hypothesis development, this study proposes a conceptual model that describes the relationship between cost efficiency, travel time, characteristics of goods, load capacity, route optimization, and transportation mode selection as shown in Figure 1.

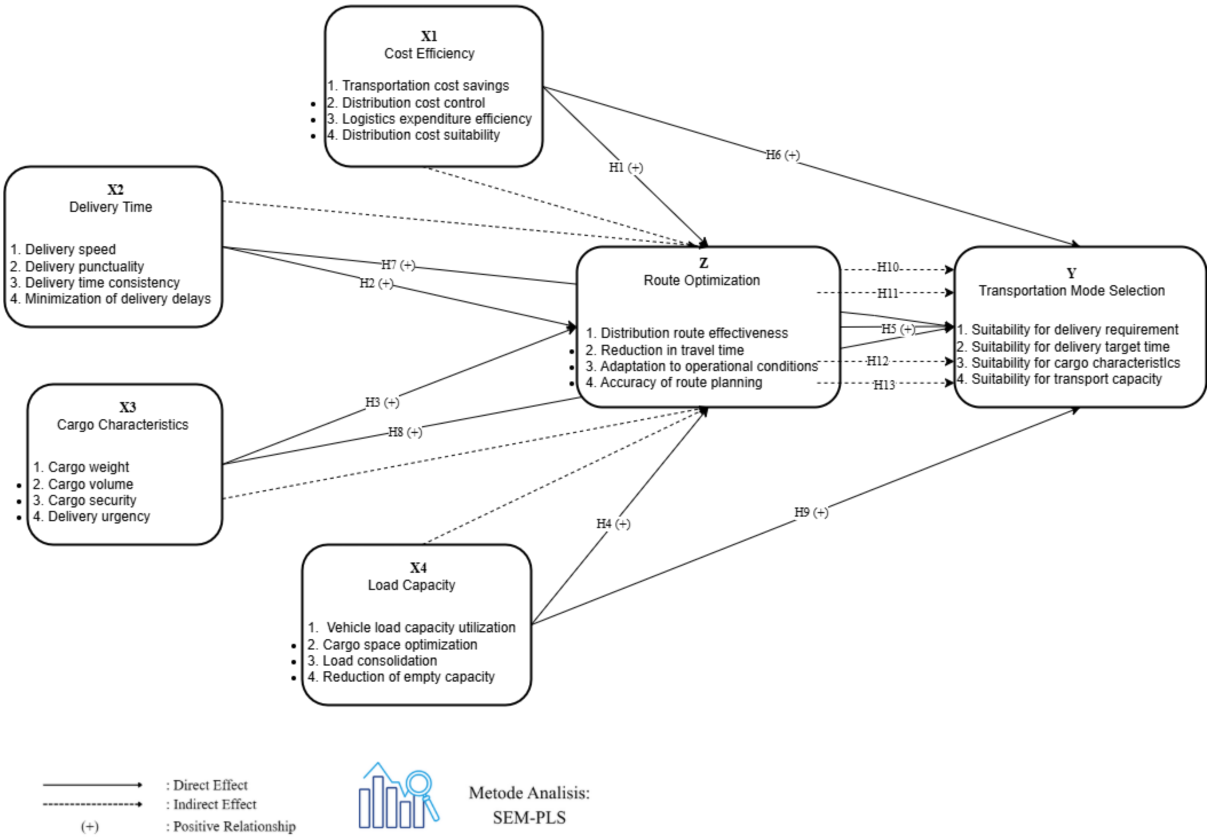

Image 1 Research Framework

Figure 1 shows that this study examines the influence of cost efficiency, travel time, characteristics of goods, and load capacity on the selection of transportation modes, either directly or through route optimization as a mediating variable. The conceptual model is the basis for hypothesis testing using the *Structural Equation Modeling–Partial Least Squares* (SEM-PLS) approach.

METHOD

Types of Research

This study uses a quantitative approach with an explanatory research method. The quantitative approach is used because the research aims to test the causal relationship between cost efficiency, travel time, characteristics of goods, load capacity, route optimization, and transportation mode selection through hypothesis testing using numerical data. According to Creswell (2018), quantitative research is an approach used to test theories by measuring relationships between variables through research instruments and analyzing data using statistical techniques. Meanwhile, explanatory research aims to explain the causal relationship between variables based on previously developed theories (Sugiyono, 2023).

This study uses a causal research design because it aims to analyze the direct and indirect influence between independent variables on dependent variables through mediation variables.

The intervariable relationship model was analyzed using *the Structural Equation Modeling–Partial Least Squares* (SEM-PLS) approach.

Place and Time of Research

This research was carried out at PT Pos Indonesia Regional III Bandung 40004, which is one of the operational units of PT Pos Indonesia which is responsible for managing distribution and logistics services in the West Java region. The research location was chosen because it has operational characteristics involving various alternative modes of transportation, distribution route management, and logistics activities that are in accordance with the research focus on factors that affect the selection of transportation modes.

The data used in this study consisted of primary data and secondary data. Secondary data in the form of operational documents of PT Pos Indonesia Regional III Bandung 40004 was collected for the operational period of 2025, which includes data on distribution volume, distribution costs, minimum charge of transportation vendors, the level of delivery timeliness (Service Level Agreement / SLA), and vehicle capacity utilization (load factor). Meanwhile, primary data was collected in the period from January to March 2026 through field observations, semi-structured interviews with informants involved in distribution operations, and distribution of questionnaires to respondents who met the research criteria. All data obtained were then analyzed using the Structural Equation Modeling method based on Partial Least Squares (SEM-PLS) to test the relationship between variables in the study.

Population and Sample

The population in this study is all employees of PT Pos Indonesia Regional III Bandung 40004 who are directly involved in distribution operational activities, transportation planning, distribution route management, and decision-making related to the selection of transportation modes.

The sampling technique uses purposive sampling, which is a technique for determining samples based on certain criteria according to the research objectives (Sugiyono, 2023). This technique was chosen because not all members of the population have knowledge or involvement in the process of distributing goods. The criteria for respondents in this study include:

1. Employees involved in distribution or logistics activities.
2. Employees who understand the process of selecting modes of transportation.
3. Employees who have work experience according to the field of distribution operations.

The determination of the number of samples refers to the recommendations of Hair et al. (2022) who stated that research with the SEM-PLS approach requires a minimum sample count of five to ten times the number of indicators used in the research model. Considering that this study uses 24 indicators, the number of samples has met the minimum requirements so that it is able to produce stable and reliable model estimates.

Data Collection Techniques

This study uses primary data and secondary data. Primary data was obtained directly from respondents through the distribution of questionnaires, while secondary data was obtained from company documents, operational reports, scientific literature, books, and relevant previous research results.

Data collection techniques are carried out through several methods, namely:

1. Observations are carried out to obtain an overview of the distribution process of goods, transportation activities, and operational conditions of the company.

2. Interviews were conducted with authorities in the field of logistics and transportation to obtain information about distribution policies and the process of selecting transportation modes.
3. Documentation is carried out by collecting company operational data, such as distribution cost data, load capacity, delivery performance, and other supporting documents.
4. Questionnaires are used as the main research instrument to measure respondents' perception of each research variable.

Research Instruments

The research instrument uses a structured questionnaire that is compiled based on the indicators of each research variable adapted from theory and previous research. All statement items are arranged using a five-level Likert Scale, namely:

Score	Category
1	Strongly Disagree
2	Disagree
3	Neutral
4	Agree
5	Strongly agree

According to Likert (1932), the Likert scale is an attitude measurement method that allows respondents to give a level of approval to each statement thereby facilitating the data quantification process.

The operational details of the variables used in this study are presented in Table 1.

Table 1 Variable Operationalization

Yes	Variabel	Concept	Indicator	Skala Ukur
1	**Efisiensi Biaya (X1)** *(Patil et al., 2023; Park et al., 2012; Meixell & Norbis, 2008)*	Cost efficiency is a company's ability to minimize transportation and distribution costs without reducing the quality of service thereby improving overall logistics performance.	1. Rate of transportation cost savings (Patil et al., 2023) 2. Ability to reduce distribution operational costs (Park et al., 2012) 3. Ability to handle logistics production (Meixell & Norbis, 2008) 4. Cost fit with distribution outcomes (Patil et al., 2023)	Likert (1–7)
2	**Waktu Tempuh (X2)** *(Rodrigue, 2022; Sharma et al., 2022; Masudin et al., 2022)*	Travel time is the duration required in the process of shipping goods from the point of origin to the destination which reflects the speed and accuracy of distribution.	1. Speed of the freight forwarding process (Rodrigue, 2022) 2. Timeliness of delivery of goods (Masudin et al., 2022) 3. Stability of delivery duration (Sharma et al., 2022) 4. Ability to minimize delivery delays (Sharma et al., 2022)	Likert (1–7)
3	**Characteristics Barang (X3)** *(Shin et al., 2019; Tagawa et*	Characteristics of goods are physical and non-physical attributes inherent	1. The effect of the weight of the goods on shipping (Samimi et al., 2011)	Likert (1–7)

Yes	Variabel	Concept	Indicator	Skala Ukur
	al., 2021; Samimi et al., 2011)	in goods that affect the handling, storage, and distribution of goods.	2. The effect of the volume of goods on distribution (Shin et al., 2019)	
			3. The level of security needs for goods (Tagawa et al., 2021)	
			4. Priority of the urgency of shipping (Samimi et al., 2011)	
4	**Kapasitas Muatan (X4)** *(Stanković et al., 2023; Lu & Wang, 2022; Rodrigue, 2022)*	Payload capacity is the level of ability of transportation equipment to transport goods optimally to improve distribution efficiency and reduce operational costs.	1. Utilization rate of transport capacity (Stanković et al., 2023)	Likert (1–7)
			2. The ability to maximize transport space (Lu & Wang, 2022)	
			3. The ability to consolidate cargo (Rodrigue, 2022)	
			4. Ability to reduce vehicle empty capacity (Stanković et al., 2023)	
5	**Optimalisasi Rute (Z)** *(Lu & Wang, 2022; Yakovlev et al., 2022; Sharma et al., 2022)*	Route optimization is the process of determining the most efficient distribution route by considering cost, time, vehicle capacity, characteristics of goods, and operational conditions to improve distribution performance.	1. Determination of the most effective distribution route (Lu & Wang, 2022)	Likert (1–7)
			2. Ability to reduce distribution mileage (Yakovlev et al., 2022)	
			3. Ability to adapt distribution routes to operational conditions (Sharma et al., 2022)	
			4. Precision of distribution route planning (Lu & Wang, 2022)	
6	**Selection of Modes of Transportation (Y)** *(Patil et al., 2023; Lu & Wang, 2022; Shin et al., 2019)*	Choosing a mode of transportation is a decision-making process in determining the most suitable type of transportation based on cost efficiency, time, characteristics of goods, and delivery needs.	1. Mode suitability to shipping needs (Patil et al., 2023)	Likert (1–7)
			2. Mode suitability with the delivery time target (Lu & Wang, 2022)	
			3. Fashion suitability with the type of item (Shin et al., 2019)	
			4. The ability of transportation modes to meet the needs of delivery capacity (Patil et al., 2023)	

Source: Processed by the author based on various references (2026).

Data Analysis Techniques

Data analysis was carried out using SmartPLS 4 software with the Structural Equation Modeling–Partial Least Squares (SEM-PLS) approach. The SEM-PLS method was chosen because it is able to test complex relationships between latent variables, accommodate models with mediating variables, and does not require strict normal data distribution (Hair et al., 2022).

The analysis stage begins with descriptive statistical analysis to describe the characteristics of respondents and the distribution of questionnaire answers. Furthermore, an evaluation of the measurement model (*outer model*) was carried out which included testing convergent validity through *loading factor* values and *Average Variance Extracted* (AVE), discriminant validity using *Fornell-Larcker* and *Heterotrait-Monotrait Ratio* (HTMT) criteria, and construct reliability using *Composite Reliability* and *Cronbach's Alpha values*.

After the measurement model meets the criteria, an evaluation of the structural model (*inner model*) is carried out through testing the determination coefficient (R^2), effect size (f^2), predictive relevance (Q^2), and model suitability index (*Standardized Root Mean Square Residual* or SRMR). Hypothesis testing was carried out using *a bootstrapping* procedure with a significance level of 5%. The hypothesis is accepted if the t-value is > 1.96 and the p-value is < 0.05. In addition to testing the direct effect, this study also tested the *indirect effect* to determine the role of route optimization as a mediating variable in the relationship between cost efficiency, travel time, characteristics of goods, load capacity, and the selection of transportation modes.

RESULTS AND DISCUSSION

Respondent Characteristics

This study involved 154 respondents who met the research criteria, namely individuals involved in distribution activities, have an understanding of the selection of transportation modes, and have work experience in the field of logistics. The characteristics of the respondents were analyzed to provide an overview of the sample profile and assess the level of data representativeness to the operational conditions of distribution at PT Pos Indonesia Regional III Bandung 40004.

Based on the results of the respondent grouping, the majority of respondents were male as many as 83 people (54%), while female respondents amounted to 71 people (46%). In terms of age, respondents were dominated by 52 people (34%) in the 36-45 year age group, followed by 45 people (29%) in the 25-35 age group, 36 people (23%) under 25 years old, and 21 people over 45 years old (14%). In terms of work experience, the majority of respondents had a working period of 4–6 years and more than 6 years with the same number, namely 59 people (38%) each, which indicates that most of the respondents have adequate experience in logistics and distribution activities. Based on the field of work, respondents were dominated by employees in the field of Business and Logistics Services as many as 62 people (40%) and Logistics Operations and Transportation as many as 48 people (31%), followed by Warehousing and Processing as many as 26 people (17%), Support and Administration as many as 13 people (8%), and other fields as many as 5 people (3%).

The composition of the respondents shows that most of the respondents are directly related to the distribution and logistics transportation activities that are the focus of the research. Thus, the data obtained is considered representative enough to describe the company's operational conditions and supports an empirical analysis of the influence of cost efficiency, travel time, characteristics of goods, and load capacity on the selection of transportation modes through route optimization as a mediating variable.

Evaluation of the Outer Model

The evaluation of *the outer model* is carried out to test the quality of the research instrument through testing the validity and reliability of the construct. This test aims to ensure that each indicator is able to accurately and consistently measure the latent constructs it represents. The evaluation of *the outer model* in this study includes *testing convergent validity*, *discriminant validity*, and construct reliability through *Composite Reliability*, *Cronbach's Alpha*, and *Average Variance Extracted* (AVE) values (Hair et al., 2019).

1. Convergent Validity

The *convergent validity* test was carried out by evaluating the *outer loading* value of each indicator. According to Hair et al. (2019), an indicator is declared to meet the convergence validity if it has *an outer loading* value greater than 0.70. The higher the *outer loading value,* the better the indicator's ability to represent the latent construct being measured.

Table 2 Convergent Validity Test Results

	EB_X1	WT_X2	KB_X3	KM_X4	PMT_Y	OR_Z	Standard	Status
X1.1	,837						> 0,70	Valid
X1.2	,806						> 0,70	Valid
X1.3	,829						> 0,70	Valid
X1.4	,846						> 0,70	Valid
X2.1		,824					> 0,70	Valid
X2.2		,841					> 0,70	Valid
X2.3		,843					> 0,70	Valid
X2.4		,828					> 0,70	Valid
X3.1			,831				> 0,70	Valid
X3.2			,804				> 0,70	Valid
X3.3			,828				> 0,70	Valid
X3.4			,815				> 0,70	Valid
X4.1				,795			> 0,70	Valid
X4.2				,864			> 0,70	Valid
X4.3				,810			> 0,70	Valid
X4.4				,840			> 0,70	Valid
Y1					,810		> 0,70	Valid
Y2					,775		> 0,70	Valid
Y3					,852		> 0,70	Valid
Y4					,839		> 0,70	Valid
Z1						,817	> 0,70	Valid
Z2						,851	> 0,70	Valid
Z3						,838	> 0,70	Valid
Z4						,768	> 0,70	Valid

Source: Processed by Researchers with SmartPLS3 Application, 2026

Based on Table 2, all indicators in the variables of Cost Efficiency (X1), Travel Time (X2), Goods Characteristics (X3), Load Capacity (X4), Route Optimization (Z), and Transportation Mode Selection (Y) have an *outer loading* value above the required minimum limit, which is 0.70. The *outer loading* value ranges from 0.768 to 0.864, which indicates that each indicator has a strong correlation level to the construct it represents.

In the Cost Efficiency variable (X1), *the outer loading* value is in the range of 0.806–0.846, which indicates that all indicators are able to represent the cost efficiency construct well. The Travel Time variable (X2) has an *outer loading* value between 0.824–0.843, while the Goods Characteristics variable (X3) shows a value between 0.804–0.831. All indicators in the two variables met the criteria of convergent validity and were able to adequately explain latent constructs.

Furthermore, the Load Capacity (X4) variable has an *outer loading* value between 0.795–0.864, while the Transportation Mode Selection variable (Y) shows a value between 0.775–0.852. In the Route Optimization variable (Z), *the outer loading* value ranges from 0.768–0.851. Although the Z4 indicator has the lowest *outer loading* value compared to other indicators, it is still above the recommended minimum limit so it is still valid.

Overall, the results of *the convergent validity* test showed that all research indicators met the convergent validity criteria. Thus, all indicators are declared valid and able to represent the latent construct measured so that they are suitable for use in the next stage of analysis.

2. Discriminant Validity

Discriminant validity *testing* was carried out using *the Fornell-Larcker Criterion* method. This test aims to ensure that each construct has an adequate degree of difference with the other constructs so that each latent variable is able to represent a different concept in the research model. According to Fornell and Larcker (1981), a construct is declared to meet *discriminant validity* if the square root value *of Average Variance Extracted* (AVE) is greater than the correlation value of the construct with other constructs.

Table 3 Results of the discriminant validity test (Fornell-Lacker)

	EB_X1	KM_X4	KB_X3	OR_Z	PMT_Y	WT_X2	Status
EB_X1	0,830						Valid
KM_X4	0,124	0,828					Valid
KB_X3	0,144	0,246	0,820				Valid
OR_Z	0,466	0,630	0,570	0,819			Invalid
PMT_Y	0,421	0,611	0,622	0,827	0,819		Invalid
WT_X2	0,124	0,210	0,210	0,514	0,482	0,834	Valid

Source: Processed by Researchers with SmartPLS3 Application, 2026

Source: Processed using SmartPLS 3, 2026.

Based on Table 3, most of the research constructs have met the *criteria of discriminant validity*. The variables Cost Efficiency (X1), Travel Time (X2), Goods Characteristics (X3), and Payload Capacity (X4) have greater square root values of AVE than correlation with other constructs. These results show that each construct has a good ability to distinguish itself from other constructs in the research model.

However, in the variables of Route Optimization (Z) and Transportation Mode Selection (Y), it was found that the correlation value between constructs was 0.827 which was higher than the square root value of AVE for each construct, which was 0.819. This condition indicates that the two constructs have not fully met the criteria of *discriminant validity* based on the *Fornell-Larcker Criterion approach*.

Nonetheless, the high correlation between Route Optimization and Transportation Mode Selection can be explained conceptually because the two variables have a close relationship in the logistics distribution system. Route optimization is one of the factors that directly affect the effectiveness of decision-making in choosing transportation modes. In addition, the results of *the convergent validity* test showed that all indicators had *an outer loading* value above 0.70 and all constructs met the required reliability criteria. Therefore, the research model is still considered feasible to proceed to the testing stage of the structural model (*inner model*) while still paying attention to the conceptual proximity between the two constructs.

3. Reliability dan Average Variance Extracted (AVE)

Construct reliability testing is performed to ensure the level of internal consistency of each latent variable in measuring the concept being studied. In a study based on *Structural Equation Modeling–Partial Least Squares* (SEM-PLS), the reliability of the construct was evaluated using *Cronbach's Alpha* and *Composite Reliability* values. A construct is declared reliable if it has *Cronbach's Alpha* and *Composite Reliability* values greater than 0.70 (Hair et al., 2019). In addition, the validity of the convergence is also evaluated using *the Average Variance Extracted* (AVE) value, where an AVE value greater than 0.50 indicates that the construct is able to explain more than 50% of the variance of the indicator it measures (Fornell & Larcker, 1981).

Table 4 Reliability and AVE Test Results

	Cronbach's Alpha	*rho_A*	*Composite Reliability*	*Average Variance Extracted* (AVE)
EB_X1	0,850	0,858	0,898	0,688
KM_X4	0,847	0,851	0,897	0,685
KB_X3	0,838	0,843	0,891	0,672
OR_Z	0,836	0,837	0,891	0,671
PMT_Y	0,836	0,840	0,891	0,671
WT_X2	0,854	0,855	0,901	0,696

Source: Processed by Researchers with SmartPLS3 Application, 2026

Based on Table 4, the entire study construct had *a Cronbach's Alpha* value above 0.70, which ranges from 0.836 to 0.854. The results show that each construct has a good level of internal consistency in measuring the latent variables studied. The highest *Cronbach's Alpha* value was found in the Travel Time (X2) variable of 0.854, while the lowest value was found in the variables of Route Optimization (Z) and Transportation Mode Selection (Y) of 0.836. Nonetheless, the entire value is still above the recommended minimum.

The results of the *Composite Reliability* test showed that the entire construct had a value above 0.70, with a value range between 0.891 to 0.901. This value indicates that all constructs have an excellent level of reliability and are able to measure research variables consistently. The Travel Time variable (X2) has the highest *Composite Reliability* value of 0.901, while the variables Goods Characteristics (X3), Route Optimization (Z), and Transportation Mode Selection (Y) have a value of 0.891.

Furthermore, the results of the *Average Variance Extracted* (AVE) test showed that the entire construct had an AVE value above 0.50, which ranged from 0.671 to 0.696. The highest AVE value was obtained in the Travel Time (X2) variable of 0.696, while the lowest AVE value was found in the variables of Route Optimization (Z) and Transportation Mode Selection (Y) of 0.671. The results show that the entire construct is able to explain more than 50% of the variance of the indicators that make it up so that it meets the criteria of convergent validity.

Based on the results of *Cronbach's Alpha*, *Composite Reliability*, and *Average Variance Extracted* (AVE) tests, it can be concluded that all constructs in this study have met the required reliability and validity criteria. Thus, the research instrument is stated to have a good level of consistency and measurement ability so that it is suitable for further analysis on structural models (*inner models*).

Inner Model Evaluation

Internal model *evaluation* was carried out to measure the ability of the structural model to explain the relationships between the latent variables studied. The *inner model test* includes the analysis of the determination coefficient (*R Square*), the testing of the *path coefficient*, and the testing of the mediation effect. This evaluation aims to determine the level of ability of exogenous variables to explain endogenous variables and test the significance of relationships built in the research model (Hair et al., 2019).

1. R Square Determination Coefficient Analysis

The determination coefficient (*R Square*) is used to measure the ability of exogenous variables to explain endogenous variables in the research model. The higher the *value of the R Square*, the greater the model's ability to explain variations in endogenous variables. According to Hair et al. (2019), *the R Square* value of 0.75 indicates the strong category (*substantial*), 0.50 the moderate category, and 0.25 the weak category (*weak*).

Table 5 R Square Test Results

	R Square	*R Square Adjusted*
OR_Z	0,785	0,779
PMT_Y	0,779	0,772

Source: Processed by Researchers with SmartPLS3 Application, 2026

Based on Table 5, the Route Optimization variable (Z) has an R Square value of 0.785 and an R Square Adjusted value of 0.779. The results showed that the variables Cost Efficiency (X1), Travel Time (X2), Goods Characteristics (X3), and Payload Capacity (X4) were able to explain the variation in the Route Optimization variable by 78.5%, while the remaining 21.5% was explained by other factors outside the research model. This value indicates that the model has a strong ability to explain changes in the Route Optimization variable.

Furthermore, the Transportation Mode Selection variable (Y) has an R Square value of 0.779 and an R Square Adjusted of 0.772. These results show that the variables Cost Efficiency (X1), Travel Time (X2), Characteristics of Goods (X3), Load Capacity (X4), and Route Optimization (Z) are able to explain the variation in the Transportation Mode Selection variable of 77.9%, while the remaining 22.1% is influenced by other factors that are not included in the research model.

Overall, the R Square value of the two endogenous variables is above 0.75 so it is included in the strong (substantial) category. These results show that the constructed structural model has good predictive capabilities in explaining the relationship between cost efficiency, travel time, characteristics of goods, load capacity, route optimization, and transportation mode selection. Thus, the research model is considered feasible to be used in testing causal relationships between variables at a later stage.

2. Pengujian Hipotesis (Path Coefficient)

Hypothesis testing was carried out to determine the direct influence between variables in the structural model using *the bootstrapping* procedure on the *Structural Equation Modeling–Partial Least Squares* (SEM-PLS) method. The test was carried out by evaluating *the path coefficient*, *t-statistics*, and *p-values*. A relationship is declared significant if it has *a t-value* greater than 1.96 and *a p-value* of less than 0.05 at a significance level of 5% (Hair et al., 2019).

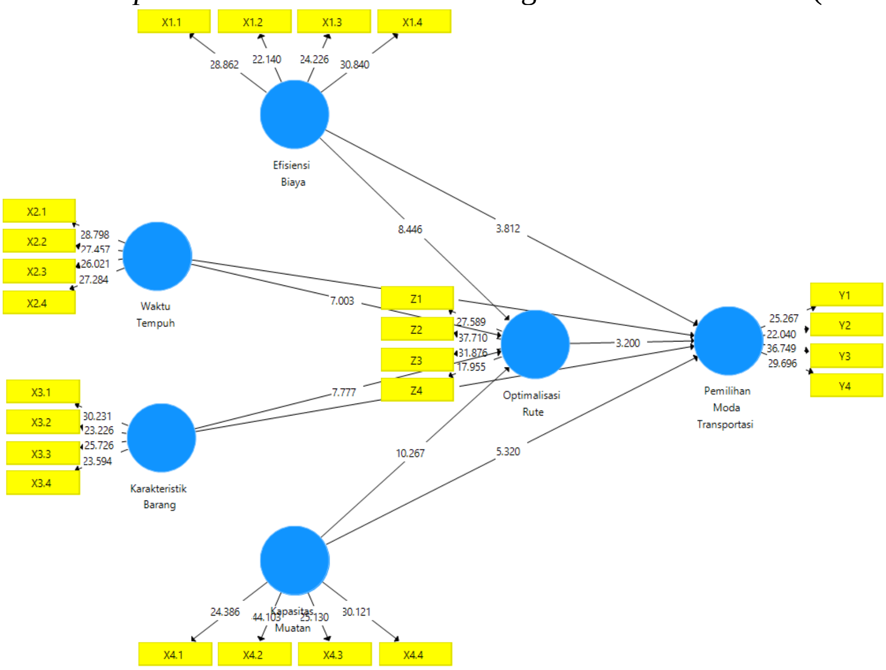

Image 2 Path Coefficients
Source: Processed by Researchers with SmartPLS3 Application, 2026

Based on *the bootstrapping* results in Figure 2, the *path coefficient*, *t-statistics*, and *p-values* values presented in Table 5 are obtained.

Table 6 Hypothesis Test Results (Path Coefficient)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
EB_X1 -> OR_Z	0,323	0,323	0,038	8,446	0,000
EB_X1 -> PMT_Y	0,191	0,194	0,050	3,812	0,000
KM_X4 -> OR_Z	0,439	0,434	0,043	10,267	0,000
KM_X4-> PMT_Y	0,300	0,301	0,056	5,320	0,000
KB_X3 -> OR_Z	0,351	0,352	0,045	7,777	0,000
KB_X3 -> PMT_Y	0,332	0,333	0,052	6,408	0,000
OR_Z -> PMT_Y	0,261	0,256	0,082	3,200	0,001
WT_X2 -> OR_Z	0,308	0,309	0,044	7,003	0,000
WT_X2-> PMT_Y	0,192	0,193	0,044	4,317	0,000

Source: Processed by Researchers with SmartPLS3 Application, 2026

Based on the test results in Table 6, all relationships between variables showed *t-values* greater than 1.96 and *p-values* less than 0.05. These results show that all hypotheses proposed in this study are accepted. Thus, all exogenous variables have a significant influence on endogenous variables according to the constructed structural model.

Cost Efficiency (X1) was proven to have a positive and significant effect on *Route Optimization* (Z) with a line coefficient value of 0.323 (*t-statistics* = 8.446; *p-values* = 0.000). These results show that the better the management of transportation and distribution costs, the higher the level of route *optimization effectiveness* implemented by the company. In addition, *Cost Efficiency* also has a positive and significant effect on *the Selection of Transportation Mode* (Y) with a line coefficient of 0.191 (*t-statistics* = 3.812; *p-values* = 0.000). These findings indicate that cost considerations are one of the important factors in determining the mode of transportation used by companies.

Travel Time (X2) has a positive and significant influence on *Route Optimization* (Z) with a path coefficient value of 0.308 (*t-statistics* = 7.003; *p-values* = 0.000). In addition, *Travel Time* also has a positive and significant effect on the *selection of Transportation Mode* (Y) with a line coefficient of 0.192 (*t-statistics* = 4.317; *p-values* = 0.000). These results show that the speed and timeliness of delivery are important considerations in the preparation of distribution routes and in the selection of the mode of transportation used.

Goods Characteristics (X3) were proven to have a positive and significant effect on *Route Optimization* (Z) with a path coefficient value of 0.351 (*t-statistics* = 7.777; *p-values* = 0.000). *Characteristics of Goods* also have a positive and significant effect on *the Selection of Transportation Mode* (Y) with a path coefficient of 0.332 (*t-statistics* = 6.408; *p-values* = 0.000). These findings suggest that the characteristics of goods such as weight, volume, level of safety, and urgency of delivery influence the company's decision in determining the most appropriate distribution route and mode of transportation.

Load Capacity (X4) showed a positive and significant influence on *Route Optimization* (Z) with a line coefficient value of 0.439 (*t-statistics* = 10.267; *p-values* = 0.000). This value is the largest coefficient compared to other relationships, thus showing that *Payload Capacity* is the most dominant factor in influencing *Route Optimization*. In addition, *Load Capacity* also has a positive and significant effect on *the Selection of Transportation Mode* (Y) with a line coefficient of 0.300 (*t-statistics* = 5.320; *p-values* = 0.000). These results indicate that the level of vehicle capacity utilization is one of the main considerations in improving distribution efficiency and determining the mode of transportation used.

Furthermore, *Route Optimization* (Z) was proven to have a positive and significant effect on the *Selection of Transportation Mode* (Y) with a line coefficient value of 0.261 (*t-statistics* = 3.200; *p-values* = 0.001). These results show that the more effective the company's planning and management of distribution routes, the more appropriate decisions are made in choosing transportation modes that support the efficiency and effectiveness of the distribution process.

Overall, the results of the *path coefficient* test showed that all research variables had a positive and significant influence according to the hypothetical relationship direction. These findings confirm that *Cost Efficiency*, *Travel Time*, *Goods Characteristics*, and *Load Capacity* are important factors that affect *Route Optimization* and *Transportation Mode Selection* at PT Pos Indonesia Regional III Bandung, both directly and through the relationship mechanism built in the research model.

3. Mediation Effect Analysis

Mediation effect testing was carried out to determine the role of Route Optimization (Z) in mediating the relationship between Cost Efficiency (X1), Travel Time (X2), Goods Characteristics (X3), and Load Capacity (X4) on Transportation Mode Selection (Y). The test was carried out using *the bootstrapping* procedure in SEM-PLS by evaluating *the indirect effect values*, *t-statistics*, and *p-values*. The mediation effect was declared significant if the t-value was greater than 1.96 and the p-values were less than 0.05 (Hair et al., 2019).

Table 7 Indirect Effect Test Results

	Original Sample (O)	*Sample Mean* (M)	*Standard Deviation (STDEV)*	*T Statistics* (|O/STDEV|)	*P Values*
EB_X1 -> OR_Z -> PMT_Y	0,084	0,083	0,030	2,812	0,005
KM_X4 -> OR_Z -> PMT_Y	0,115	0,111	0,038	3,002	0,003
KB_X3 -> OR_Z -> PMT_Y	0,092	0,089	0,029	3,106	0,002
WT_X2-> OR_Z -> PMT_Y	0,081	0,079	0,027	2,964	0,003

Source: Processed by Researchers with SmartPLS3 Application, 2026

Based on the test results in Table 7, all indirect influence pathways showed *t-statistical* values greater than 1.96 and *p-values* less than 0.05. These results show that *Route Optimization* (Z) is proven to significantly mediate the relationship between *Cost Efficiency*, *Travel Time*, *Goods Characteristics*, and *Load Capacity* on *the Selection of Transportation* Modes.

Cost Efficiency (X1) has a positive and significant indirect influence on the *Selection of Transportation Modes* (Y) through *Route Optimization* (Z) with a coefficient value of 0.084 (*t-statistics* = 2.812; *p-values* = 0.005). These results show that the influence of cost efficiency on the decision to choose the mode of transportation occurs not only directly, but also through increased effectiveness of planning and management of distribution routes.

Travel Time (X2) also shows a positive and significant indirect influence on the *Selection of Transportation Mode* (Y) through *Route Optimization* (Z) with a coefficient value of 0.081 (*t-statistics* = 2.964; *p-values* = 0.003). These findings indicate that the company's ability to optimize distribution routes contributes to increasing the accuracy of selecting transportation modes that are able to support the delivery time target.

Characteristics of Goods (X3) have a positive and significant indirect influence on the *Selection of Transportation Modes* (Y) through *Route Optimization* (Z) with a coefficient value of 0.092 (*t-statistics* = 3.106; *p-values* = 0.002). These results show that the characteristics of the goods distributed will influence the route planning process which ultimately has an impact on the decision to choose the mode of transportation that best suits the needs of the shipment.

Furthermore, *Load Capacity* (X4) shows a positive and significant indirect influence on the *Selection of Transportation Mode* (Y) through *Route Optimization* (Z) with a coefficient value of 0.115 (*t-statistics* = 3.002; *p-values* = 0.003). The value of the coefficient is the largest compared to other mediation channels, which shows that *Route Optimization* has the strongest role in bridging the relationship between *Load Capacity* and *Transportation Mode Selection*. These findings indicate that optimal utilization of vehicle capacity can increase the effectiveness of route planning so as to support more efficient transportation mode selection decisions.

Overall, the results of the *indirect effect* test showed that *Route Optimization* played a significant mediating variable in the relationship between distribution operational factors and *Transportation Mode Selection*. These findings confirm that the decision to choose a mode of transportation is not only directly influenced by *Cost Efficiency*, *Travel Time*, *Goods Characteristics*, and *Load Capacity*, but also through the company's ability to optimize distribution routes. Thus, *Route Optimization* is an important mechanism that strengthens the effectiveness of the distribution system and transportation decision-making at PT Pos Indonesia Regional III Bandung.

CONCLUSION

This study succeeded in achieving the research objective, which is to analyze the influence of cost efficiency, travel time, characteristics of goods, and load capacity on the selection of transportation modes by considering the role of route optimization as a mediating variable in PT Pos Indonesia Regional III Bandung 40004. The results of the analysis show that cost efficiency, travel time, characteristics of goods, and load capacity have a significant effect on route optimization and transportation mode selection. In addition, route optimization has been proven to play a role as a mediating variable that strengthens the relationship between these operational factors and the decision to choose a mode of transportation. These findings show that improving the quality of route planning is an important factor in supporting decisions to choose more effective and efficient modes of transportation.

Theoretically, this study enriches the development of a model of transportation mode selection by showing that route optimization functions not only as an operational aspect, but also as a mediation mechanism that explains the relationship between cost efficiency, travel time, characteristics of goods, load capacity, and transportation mode selection. Thus, this study provides a more comprehensive perspective than previous research which generally only tests the direct influence between variables.

Practically, the results of the study imply that logistics companies need to integrate distribution cost control, delivery time management, adjustment of goods characteristics, vehicle capacity optimization, and route planning in an integrated decision-making process. This approach has the potential to improve operational efficiency, improve vehicle utilization, reduce distribution costs, and improve delivery timeliness.

This research is limited to one logistics company so the results cannot be generalized to all logistics sectors. Therefore, further research is suggested to involve more diverse research objects and add other variables, such as service quality, logistics digitalization, sustainability (*green logistics*), or distribution risk management, so that the model of selecting transportation modes can be developed more comprehensively.

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