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ARTICLE

Segmenting freight operations for route choice analysis: A cluster analysis of truck transport in Bataan, Philippines

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ABSTRACT

Freight operations differ in trip conditions, transport costs, shipment characteristics, organizational arrangements, and willingness to pay for new infrastructure. This study applied K-means clustering to the most recent trips reported by 358 freight respondents in Bataan, Philippines, to identify operational segments relevant to the proposed Bataan–Cavite Interlink Bridge (BCIB). Seven standardized variables were analyzed: heavy-goods-vehicle route distance, reported travel time, toll cost, fuel cost, cargo weight, cargo value, and direct stated BCIB willingness to pay (WTP). Candidate solutions with two to eight clusters were evaluated using internal-validation criteria and stability assessments. A three-cluster solution was retained based on validation performance, parsimony, stability, and interpretability. The retained solution had the highest average silhouette coefficient among candidates (0.218). Across 200 repeated 80% subsamples, the mean adjusted Rand index (ARI) was 0.931; 100 random-seed runs produced identical partitions (ARI = 1.000). These findings support a reproducible exploratory segmentation, although separation among freight operations was limited. The identified segments were Short-Haul Lower-Cost Freight Operators (43.0%), High-Value Hazardous Full-Truckload (FTL) Freight Operators (3.6%), and Long-Haul High-Cost Heavy-Freight Operators (53.4%). The specialized high-value segment had the highest cluster-level silhouette coefficient; all 13 observations involved hazardous cargo and full-truckload operations, and the segment had the highest mean direct BCIB WTP. External profiling identified associations with commodity type, hazardous status, truckload type, axle count, truck configuration, truck ownership, and route decision authority. The findings demonstrate interpretable heterogeneity in freight operations and provide an exploratory basis for considering differentiated freight-user profiles in BCIB corridor and toll planning.

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INTRODUCTION

Regional economic productivity, manufacturing activity, and logistics performance are closely influenced by the efficiency of freight transportation systems (World Bank Group 2018). In the Philippines, inland freight movement remains highly dependent on road-based transport, which connects production areas, special economic zones, ports, airports, and distribution centers across Luzon (Suarez et al. 2022). Congestion, fuel consumption, toll expenditures, truck restrictions, and infrastructure constraints can increase operating costs and reduce logistics efficiency (Suarez et al. 2022; Vallejos and Fillone 2026). Philippine evidence indicates that road freight transport costs are relatively high within Southeast Asia, with an estimated unit transport cost of approximately 9.7 US cents per ton-km and an observed association between freight costs and road infrastructure conditions, particularly expressway-network development (Suarez et al. 2022).

Truck route choice is heterogeneous and can vary across driver, vehicle, trip, and organizational conditions. Truck-routing decisions have been shown to depend on factors beyond travel time and cost, including shipment characteristics, road type, delay, employment arrangements, routing authority, and responsibility for fuel and toll expenditures (Sun et al. 2013). Large-truck route choice has also been associated with road and trip attributes such as route distance, road width, toll-road use, and turning movements, while route-choice heterogeneity has been observed across vehicle types, trip timing, and trip purposes (Ma et al. 2025). These findings indicate that freight operators cannot necessarily be represented adequately as a single homogeneous user group. Freight valuation research provides further evidence of heterogeneity in freight decision-making. Freight value-of-time (VOT) estimates have been reported to vary according to decision-maker type, transport distance, commodity category, cargo value, and freight mode (Tao and Zhu 2020). Substantial variation in the value of freight travel time savings has likewise been reported across transport modes and respondent types (Binsuwadan et al. 2022).

KEYWORDS

freight transport; K-means clustering; freight segmentation; truck operations; willingness to pay; toll infrastructure; Bataan–Cavite Interlink Bridge

Organizational and vehicle characteristics provide additional sources of freight heterogeneity. Company truck drivers and owner-operators have also been examined using stated-preference scenarios involving toll-lane use, travel time, reliability, and safety, illustrating the importance of considering organizational context when studying truck-route decisions (Kim and Arroyo Turcios 2023). In related Philippine research, truck characteristics, payload, and load-management conditions were associated with freight fuel efficiency and operating performance (Vallejos and Fillone 2026). Together, these studies indicate that freight operations differ not only in route characteristics but also in vehicle, shipment, cost, and organizational conditions.

Traditional freight route-choice studies commonly use econometric and discrete-choice models to estimate how travel time, monetary cost, and other attributes influence the choice among transport alternatives. Freight value-of-time research commonly examines monetary valuations derived from the estimated time and cost parameters of behavioral choice models (Tao and Zhu 2020; Binsuwadan et al. 2022). Unsupervised clustering addresses a different but complementary analytical question: whether observations can be grouped into internally similar segments based on multiple measured characteristics (Jain 2010). K-means clustering is suitable for this purpose because it partitions observations according to multivariate similarity while minimizing within-cluster variation. In freight applications, such segmentation can reveal combinations of operational, shipment, cost, and infrastructure-valuation characteristics that may not be apparent from aggregate descriptive statistics alone.

The proposed Bataan–Cavite Interlink Bridge (BCIB) provides a relevant setting for examining such freight heterogeneity. The project is intended to establish a direct road connection across Manila Bay between Bataan and Cavite and improve interregional accessibility between Central Luzon and Southern Luzon (DPWH 2023). A new tolled connection may change route distance, travel time, operating expenditures, and network accessibility for freight movements. However, the practical importance of these changes is unlikely to be uniform across freight operations because operators differ in shipment characteristics, vehicle requirements, existing cost exposure, and route-decision arrangements (Sun et al. 2013; Kim and Arroyo Turcios 2023; Tao and Zhu 2020).

Despite the importance of freight heterogeneity, the multidimensional segmentation of truck freight operations in Bataan remains insufficiently examined in the local research discussed here. Earlier research in the same freight corridor examined toll-road route choice using operator and trip characteristics but did not identify multivariate operational freight segments through unsupervised clustering (Vallejos et al. 2024). The present study addresses this gap by applying multivariate clustering to validated freight-operation data from Bataan, integrating trip, operating-cost, shipment, and direct stated BCIB WTP characteristics. This study contributes to freight transportation research in three ways. First, it identifies freight-operation segments using multiple dimensions of existing operations, shipment characteristics, and stated toll willingness. Second, it evaluates the robustness of the segmentation using complementary validation, sensitivity, and stability assessments. Third, it extends cluster interpretation beyond the clustering inputs by examining external commodity, shipment, vehicle, ownership, and route-decision characteristics. Accordingly, this study aims to: (1) identify distinct freight-operation segments among truck transport respondents in Bataan; (2) assess the internal validation measures and robustness of the resulting cluster solution; (3) characterize the identified clusters using external commodity, shipment, vehicle, ownership, and route-decision characteristics; and (4) examine the implications of the resulting freight segments for BCIB toll and corridor planning. The analysis is exploratory rather than causal and is intended to characterize freight heterogeneity rather than predict future BCIB use.

MATERIALS AND METHODS

Study area and Data Collection

The study focused on freight operations originating in Bataan, Philippines, a province in Central Luzon characterized by industrial, port-related, and logistics activities. Freight movements from Bataan connect with major corridors serving Metro Manila, Pampanga, Bulacan, Subic, Cavite, and other parts of Luzon. Truck transport operations in the province support the movement of industrial products, construction materials, agricultural goods, petroleum products, and other commercial cargo, providing a heterogeneous freight-operating environment relevant to route and infrastructure planning (Vallejos et al. 2024). The study was situated in the context of the proposed BCIB, an approximately 32.15-km road connection across Manila Bay between Mariveles, Bataan, and Naic, Cavite (DPWH 2023). On the Bataan side, the project approach is situated in the Alas Asin–Mountain View area of Mariveles, while the Cavite approach connects to the road network in Naic. The alignment passes near Corregidor Island, where a turnaround facility is incorporated to accommodate a possible future connection to the island; this future access is not part of the present BCIB mainline project (DPWH 2023). Figure 1 presents the geographic context and schematic alignment of the proposed BCIB, which provides the infrastructure context for the direct stated willingness-to-pay (WTP) question used in the clustering analysis.

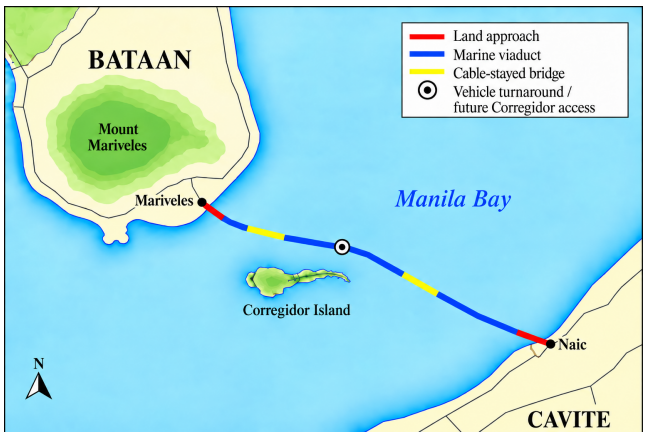


Figure 1: Geographic context and schematic alignment of the proposed Bataan–Cavite Interlink Bridge (BCIB), from Mariveles, Bataan to Naic, Cavite. Prepared by the authors based on the BCIB Final Updated Environmental Impact Assessment (DPWH 2023).

Data were obtained through a structured freight survey administered through face-to-face interviews. Fieldwork was conducted over 12 weeks, from May to July 2023, across municipalities in Bataan with substantial freight transport activity. Participation was voluntary, informed consent was obtained, and responses were anonymized to protect respondent confidentiality. Respondents included truck drivers, shipper/company owners or managers, and freight forwarders. Purposive sampling was used because respondents were required to be directly involved in freight movements originating in Bataan. Truck drivers were interviewed at locations where truckers commonly stayed, waited, or gathered during freight operations, whereas shipper/company owners or managers and freight forwarders were interviewed at their respective offices. Field data collection initially targeted approximately 300 truck drivers to provide a practical analytical sample of active freight operators. Additional shipper/company owners or managers and freight forwarders were recruited because

these stakeholders may also participate in route, shipment, and transport-cost decisions. The final analytical dataset comprised 358 cleaned and validated responses, consisting of 300 truck drivers, 23 company owners, and 35 freight forwarders. Thus, 358 represented the final achieved analytical sample rather than a statistically predetermined sample-size target.

For the trip-level questions, respondents reported information on their most recent completed freight trip, including trip origin and destination, trip start and end times, waiting or rest time, toll expenditure, fuel expenditure, cargo weight, cargo value, and related shipment and vehicle characteristics. The survey also collected information on route decision-making and responsibility for transport costs. Reported origins and destinations were validated and used to obtain heavy-goods-vehicle (HGV) route distances from the freight-routing dataset. Travel time was calculated as the difference between the reported trip end and start times, minus the reported waiting or rest time. Reported toll cost, fuel cost, cargo weight, and cargo value were retained as respondent-reported trip and shipment characteristics following data cleaning and validation. The survey also included a direct hypothetical question concerning use of the proposed BCIB. Respondents were asked to consider the BCIB as an alternative route for trips toward Southern Luzon under the projected reduction in Bataan–Cavite travel time from five hours to 45 minutes, equivalent to approximately 4.25 hours of travel-time savings (DPWH, 2023). Respondents then stated the maximum toll amount they would be willing to pay to use the bridge. All 358 respondents provided a toll amount, and this value was used as the direct BCIB WTP variable in the clustering analysis. All 358 validated respondents also had complete observations for the other six clustering variables; accordingly, no observations were excluded because of missing values in the seven variables used for clustering.

Clustering Variables and Preprocessing

Seven numerical variables were selected to represent complementary dimensions of freight operations, shipment characteristics, and stated infrastructure valuation. The first six variables represented trip, operating-cost, and shipment conditions, whereas direct BCIB WTP represented the respondent's stated maximum toll willingness under the direct hypothetical bridge-use question. It was therefore not interpreted as revealed-preference behavior, an observed bridge-use decision, or a formal estimate of the value of freight travel-time savings. The seven variables used in the clustering analysis are summarized in Table 1.

Table 1: Variables included in the clustering analysis.

Variable	Description	Unit
HGV route distance	HGV route distance between reported trip origin and destination	km
Travel time	Trip duration calculated from reported end and start times, minus reported waiting or rest time	hours
Toll cost	Toll expenditure associated with the trip	PHP
Fuel cost	Fuel expenditure associated with the trip	PHP
Cargo weight	Weight of transported cargo	t
Cargo value	Estimated monetary value of transported cargo	PHP
Direct BCIB WTP	Maximum toll amount stated by the respondent for using the proposed BCIB under the direct hypothetical bridge-use question	PHP

The data were screened for completeness, implausible values, outliers, skewness, and inter-variable correlation before clustering. Extreme observations were reviewed against the underlying survey records rather than being removed automatically. Thirteen cargo-value observations exceeding the upper outlier threshold (Q3 + 3 × IQR) were retained because they represented verified high-value freight movements, predominantly petroleum-related hazardous shipments. One high fuel-cost observation was likewise retained after verification as a valid operating case. These observations were retained rather than automatically deleted or winsorized, while the sensitivity of the clustering results to alternative preprocessing specifications was examined separately.

Preprocessing sensitivity was evaluated before standardization because highly skewed variables can influence Euclidean-distance clustering. A broad logarithmic transformation did not consistently improve the distributions of the clustering variables. Two alternative specifications were evaluated: logarithmic transformations of both fuel cost and cargo value, and a logarithmic transformation of cargo value alone. The validated, untransformed variables were retained for the final specification because the extreme cargo values represented verified freight movements and absolute cargo value was considered relevant to the intended segmentation; the variables were subsequently standardized. Because the seven clustering variables were measured in different units and numerical ranges, all variables were standardized using Z-scores:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$$

where z_{ij} is the standardized value of variable j for respondent i, x_{ij} is the observed value of variable j for respondent i, μ_j is the mean of variable j, and σ_j is the standard deviation of variable j. Standardization placed the variables on comparable scales and prevented variables with larger numerical magnitudes from disproportionately influencing the Euclidean-distance calculations used by K-means clustering (Jain 2010). Pairwise Pearson correlations were also examined before clustering to identify potentially redundant variables. The correlation structure was considered together with the substantive role of each variable in representing trip, operating-cost, shipment, and stated WTP characteristics. No variable was removed solely on the basis of pairwise correlation.

K-means specification, validation, and stability

K-means clustering was applied to the seven standardized variables to identify freight-operation segments with similar multivariate characteristics. Data preprocessing, K-means clustering, cluster validation, stability assessments, and visualization were performed using Python 3.13.9 and scikit-learn 1.7.2 in the Anaconda environment through Jupyter Notebook. The algorithm partitions observations into K clusters and iteratively assigns observations to cluster centroids so that within-cluster variation is minimized. The K-means objective function is

$$J(C) = \sum_{k=1}^{K} \sum_{x_i \in C_k} \| x_i - \mu_k \|^2$$

where K is the number of clusters, C_k represents the set of observations assigned to cluster k, x_i is observation i, and μ_k is the centroid of cluster k. K-means therefore seeks a partition characterized by relatively small within-cluster squared Euclidean distances (Jain 2010). Candidate solutions from $k=2$ through $k=8$ were estimated using K-means with 50 centroid initializations per fit (n_init = 50), and a fixed random_state = 42 was used for the reference candidate solutions. After the three-cluster solution was retained, the final k=3 model was re-estimated using 100 centroid initializations (n_init = 100) with random_state = 42. The number

of clusters was not determined using a single validation statistic. Instead, within-cluster sum of squares, average silhouette coefficient, Calinski–Harabasz (CH) index, Davies–Bouldin (DB) index, parsimony, substantive interpretability, and stability were considered jointly. Cluster cohesion and separation were evaluated using the silhouette coefficient:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

where a(i) is the average dissimilarity between observation i and the other observations in its assigned cluster, and b(i) is the minimum average dissimilarity between observation i and observations belonging to another cluster. Silhouette values range from −1 to 1. Larger positive values indicate stronger correspondence with the assigned cluster, values near zero indicate observations positioned between clusters, and negative values indicate greater similarity to another cluster than to the assigned cluster (Rousseeuw 1987). No rigid silhouette threshold was used as the sole basis for determining the final number of clusters. The CH index was used as an additional measure of cluster separation relative to within-cluster dispersion, with larger values generally indicating stronger separation relative to compactness. The DB index assessed within-cluster scatter relative to separation between clusters, with smaller values indicating more compact and separated partitions. These measures were used together with the silhouette coefficient rather than as independent decision rules.

Two complementary stability assessments were conducted. First, initialization stability was assessed by rerunning the retained K-means solution using 100 different random seeds, with 50 centroid initializations per fit. Agreement between the resulting partitions and the reference solution was quantified using the adjusted Rand index (ARI). Second, sampling stability was evaluated using 200 repeated random subsamples containing 80% of the observations. For each subsample, K-means was fitted using 50 centroid initializations, and the resulting centroids were used to assign the full sample. Agreement with the full-sample reference segmentation was then evaluated using ARI. The initialization assessment examined the consistency of K-means optimization, whereas the subsampling assessment evaluated the sensitivity of cluster assignments to changes in the analytical sample. Sensitivity of cluster assignments to the alternative preprocessing specifications was also assessed using ARI to determine whether the alternative transformations produced materially different freight-segmentation structures.

The analytical procedure comprised data screening and preprocessing, Z-score standardization of the seven clustering variables, estimation of candidate K-means solutions from *k=2* to *k=8*, and joint evaluation using internal-validation, preprocessing-sensitivity, and stability measures. The retained *k=3* solution was subsequently characterized using numerical and categorical external profiles, statistical comparisons, and PCA and silhouette visualizations.

External profiling and statistical comparison

Descriptive cluster labels were assigned after model estimation by examining original-scale cluster means and medians, standardized cluster centroids, and external operational characteristics. External profiling variables were not included as inputs to K-means and therefore did not determine cluster membership. These variables included respondent category, commodity type, commodity characteristics (hazardous, temperature-controlled, perishable/time-sensitive), full-truckload/less-than-truckload (FTL/LTL) status, truck axle count, detailed truck configuration, truck ownership, route decision-maker, and toll payer. Respondent category, route decision-maker, and toll payer were treated as conceptually distinct variables because the person who completed the questionnaire was not necessarily the individual or organization responsible for selecting the route or bearing the toll expenditure.

Because several numerical variables exhibited skewed distributions and the resulting clusters differed in size, differences among clusters were evaluated using Kruskal–Wallis tests. Effect sizes were summarized using epsilon-squared (ε^2). When an omnibus test indicated a significant difference, pairwise Mann–Whitney U tests with Holm adjustment were used for follow-up comparisons. Associations between cluster membership and categorical external characteristics with sufficient variation were evaluated using chi-square statistics with 5,000-permutation p-values and Cramér's V effect sizes. Permutation-based p-values were used because several contingency tables contained sparse expected cell counts. Associations with external categorical characteristics were interpreted as exploratory, with consideration given to effect sizes and the number of statistical comparisons performed. Variables without sufficient variation across the sample were reported descriptively rather than subjected to inferential association testing. Comparisons involving the seven clustering variables were interpreted descriptively because these variables were used to construct the cluster solution.

Principal component analysis (PCA) was used only to provide a two-dimensional visualization of the seven-variable standardized feature space. PCA did not determine cluster membership and was not used to select the number of clusters (Jolliffe and Cadima 2016).

RESULTS AND DISCUSSION

Descriptive characteristics and preprocessing assessment

The analytical sample consisted of 358 respondents with complete values for all seven clustering variables. Considerable variation was observed in route distance, transport expenditure, shipment size, shipment value, and direct stated BCIB willingness to pay (WTP). HGV route distance averaged 197.9 km and ranged from 24.8 to 506.8 km, while reported travel time averaged 5.40 h and ranged from 1.5 to 12.5 h. Mean reported toll and fuel costs were PHP 831 and PHP 3,877, respectively. Mean cargo weight was 24.82 t, while mean cargo value was approximately PHP 1.27 million. Direct BCIB WTP averaged PHP 1,129.33, with a median of PHP 1,000. Descriptive statistics are presented in Table 2.

Table 2: Descriptive statistics of the seven clustering variables (N = 358).

Variable	Mean	SD	Median	Q1	Q3	Min	Max	Skewness
HGV route distance (km)	197.943	79.791	185.128	148.260	243.840	24.792	506.762	0.485
Travel time (h)	5.402	1.948	5.500	4.000	6.500	1.500	12.500	0.313
Toll cost (PHP)	831.159	464.011	800	521.5	1,052	0	2,600	0.341
Fuel cost (PHP)	3,876.536	1,945.606	3,900	2,500	4,700	1,000	14,000	1.410
Cargo weight (t)	24.821	13.226	25	15	37	1	60	0.180
Cargo value (PHP)	1,274,051.955	1,569,539.159	1,000,000	360,000	1,500,000	70,000	8,500,000	3.435
Direct BCIB WTP (PHP)	1,129.330	401.615	1,000	1,000	1,500	500	2,000	0.714

Cargo value exhibited the greatest positive skewness (3.435), followed by fuel cost (1.410). The 13 cargo-value observations identified as extreme during preprocessing were verified as legitimate high-value freight movements and were therefore retained. Pairwise correlation analysis showed the strongest association between HGV route distance and reported travel time ($r = 0.737$). Route distance was also positively associated with fuel cost ($r = 0.451$) and toll cost ($r = 0.429$), while cargo value and direct BCIB WTP had a positive correlation of $r = 0.340$. None of these pairwise correlations was considered sufficiently high to indicate redundancy requiring removal of a clustering variable.

Transformation sensitivity was examined to assess how alternative variable transformations affected the resulting cluster structure and its stability. A broad logarithmic transformation did not consistently improve the variable distributions. A targeted transformation of fuel cost and cargo value produced a different three-cluster partition relative to the primary specification and exhibited lower subsampling stability, with a mean subsampling ARI of approximately 0.650. A cargo-value-only logarithmic transformation reduced cargo-value skewness substantially but also altered cluster membership relative to the primary solution and yielded a mean subsampling ARI of approximately 0.692. Because the high cargo values were verified rather than erroneous and absolute cargo value was substantively relevant to freight segmentation, the validated, untransformed variables were retained and subsequently standardized for the final clustering specification.

Selection, validation, and stability of the three-cluster solution

The internal-validation criteria did not identify a common optimal number of clusters. The two-cluster solution produced the highest Calinski–Harabasz (CH) index (89.725), whereas the lowest Davies–Bouldin (DB) index occurred at $k = 8$ (1.312). The three-cluster solution had the highest average silhouette coefficient (0.218), although the value at $k = 5$ (0.217) was nearly identical. At $k = 3$, the DB index was 1.347, and within-cluster sum of squares decreased from 2001.539 at $k = 2$ to 1698.437. The elbow pattern was gradual rather than sharply defined, and the low silhouette values indicated weak overall cluster separation. Thus, $k = 3$ was not uniquely supported by the internal-validation indices alone. The candidate-solution results are presented in Table 3.

Table 3: Internal validation for candidate K-means solutions

k	Inertia	Silhouette	CH index	DB index
2	2001.539	0.188	89.725	1.843
3	1698.437	0.218	84.397	1.347
4	1516.104	0.212	77.045	1.424
5	1355.667	0.217	74.883	1.318
6	1198.692	0.209	76.779	1.346
7	1095.877	0.202	75.275	1.335
8	1002.289	0.214	75.014	1.312

The absence of a common optimum across the internal-validation criteria is consistent with the exploratory nature of clustering, for which no single criterion identifies a universally optimal partition (Jain 2010). Accordingly, $k = 3$ was retained based on the combined consideration of internal validation, parsimony, stability, and interpretability. Initialization stability was high: across 100 random-seed runs, the three-cluster partition remained unchanged (ARI = 1.000), indicating consistent K-means optimization rather than independently establishing distinct underlying groups. In the sampling-stability assessment, 200 repeated subsamples containing 80% of the observations yielded a mean ARI of 0.931 and a median of 0.978, with 5th and 95th percentiles of 0.650 and 1.000, respectively. Although the results indicate generally high agreement under resampling, the lower-tail ARI values reveal sensitivity in some subsamples. Thus, the stability findings support the reproducibility of the selected partition but do not eliminate the limitation of weak overall cluster separation.

The combined validation and stability results support retaining the three-cluster solution as an exploratory segmentation of freight operations. However, the overall silhouette coefficient of 0.218 indicates weak separation, suggesting substantial overlap among some observations. The selected solution should therefore be interpreted as a useful descriptive grouping rather than evidence of sharply defined freight-operation categories. Cluster-level separation and sensitivity to preprocessing are examined further in the subsequent sections. The internal-validation patterns for the candidate solutions are summarized in Figure 2.

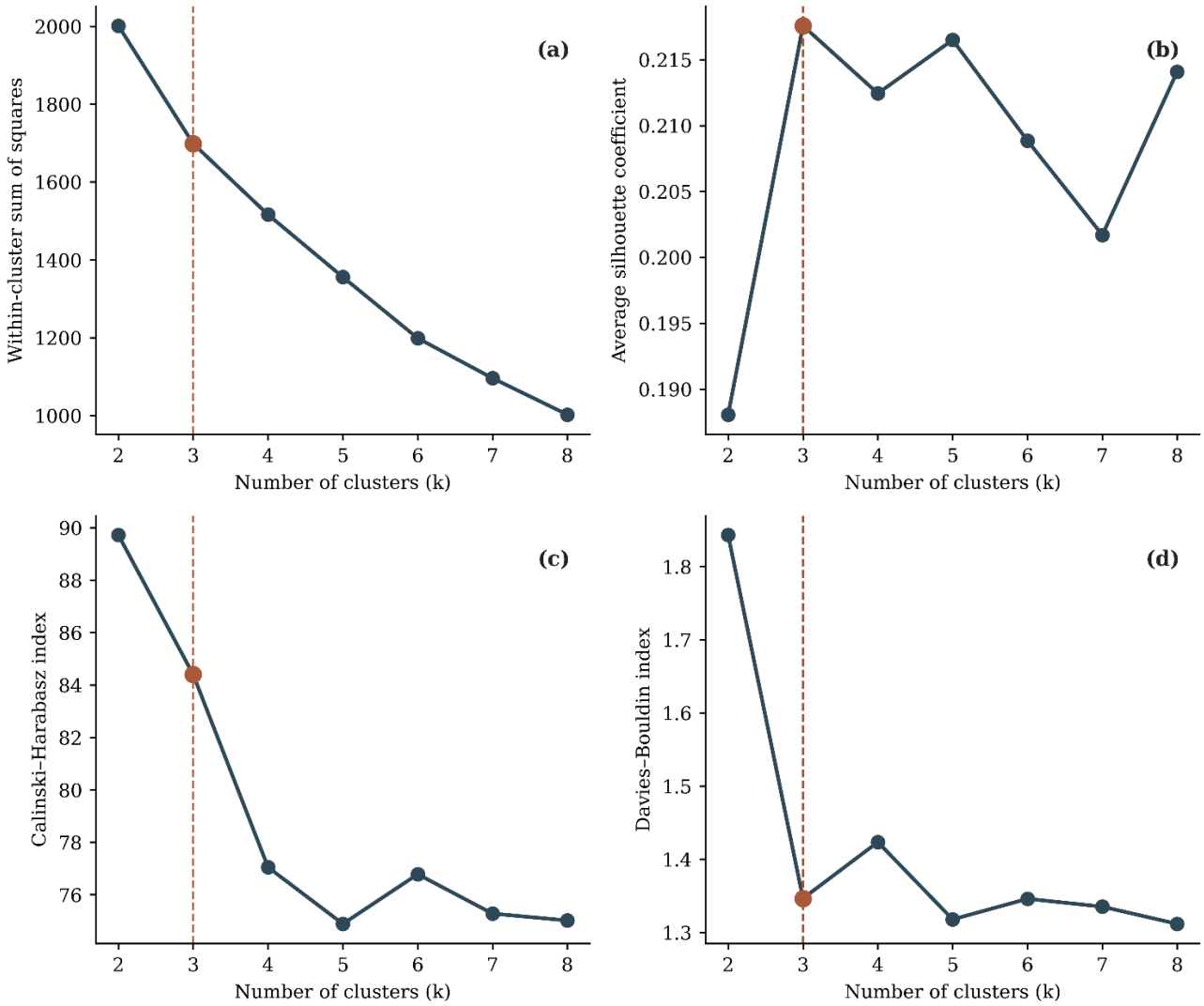


Figure 2: Internal-validation diagnostics for candidate K-means solutions: (**a**) within-cluster sum of squares, (**b**) average silhouette coefficient, (**c**) Calinski–Harabasz index, and (**d**) Davies–Bouldin index.

Final freight-operation segments

The retained solution consisted of 154 respondents in Cluster 1 (43.0%), 13 in Cluster 2 (3.6%), and 191 in Cluster 3 (53.4%). Cluster labels were assigned after estimation on the basis of original-scale profiles and external operational characteristics. The three groups were labeled Short-Haul Lower-Cost Freight Operators, High-Value Hazardous FTL Freight Operators, and Long-Haul High-Cost Heavy-Freight Operators, respectively. The numerical profiles of the three clusters, together with the corresponding Kruskal–Wallis statistics, effect sizes, and Holm-adjusted pairwise comparisons, are presented in Table 4.

Table 4: Numerical profiles and statistical differences among the final three freight clusters

Variable	Cluster 1	Cluster 2	Cluster 3	Kruskal–Wallis H	ε^2	C1–C2	C1–C3	C2–C3
HGV route distance (km)	135.45	173.25	250.01	202.675	0.565	0.004	< 0.001	< 0.001
Travel time (h)	3.91	5.38	6.61	176.393	0.491	0.001	< 0.001	0.006
Toll cost (PHP)	565.01	650.92	1,058.02	105.086	0.290	0.573	< 0.001	< 0.001
Fuel cost (PHP)	3,127.29	2,673.85	4,562.50	55.576	0.151	0.724	< 0.001	< 0.001
Cargo weight (t)	21.69	20.54	27.64	20.839	0.053	0.531	< 0.001	0.026
Cargo value (PHP)	823,961	8,392,308	1,152,464	48.516	0.131	< 0.001	0.001	< 0.001
Direct BCIB WTP (PHP)	1,102.60	1,538.46	1,123.04	18.771	0.047	< 0.001	0.655	< 0.001

Note: Cluster columns report arithmetic means in the original measurement units. ε^2 = epsilon-squared effect size. C1–C2, C1–C3, and C2–C3 are Holm-adjusted p-values from pairwise Mann–Whitney U tests; $p < 0.05$ indicates statistical significance.

Cluster 1 – Short-Haul Lower-Cost Freight Operators. Cluster 1 represented comparatively shorter and lower-cost freight movements. It had the shortest mean HGV route distance (135.45 km), shortest reported travel time (3.91 h), and lowest mean toll cost (PHP 565.01). Its mean fuel expenditure of PHP 3,127.29 was also below the overall sample mean. Mean cargo value was approximately PHP 0.824 million and mean direct BCIB WTP was PHP 1,102.60. Its principal distinguishing features were therefore the shorter scale and lower cost exposure of its current freight movements. The attractiveness of a new tolled connection to such operators would likely depend on the combination of route benefits and additional monetary cost rather than toll price alone. Truck-routing research likewise shows that route decisions are influenced by multiple attributes, including travel time, distance, delay, road type, toll amount, shipment conditions, and cost-bearing arrangements (Sun et al. 2013).

Cluster 2 – High-Value Hazardous FTL Freight Operators. Cluster 2 was the smallest segment (n = 13, 3.6%) and had the highest mean silhouette coefficient (0.702). Its mean HGV route distance was 173.25 km, longer than that of Cluster 1 (135.45 km) but shorter than that of Cluster 3 (250.01 km). Mean reported travel time was 5.38 h, while mean cargo value was approximately PHP 8.39 million, substantially exceeding those of the other clusters. Cluster 2 also had the highest mean direct BCIB WTP (PHP 1,538.46). All 13 observations involved hazardous cargo, full-truckload operations, and company-owned trucks. Petroleum products accounted for 84.6% (11 of 13) of the segment. Route decisions were made by the shipper/company owner in 84.6% of cases and by the client in 15.4%; none were driver-directed. Notably, all 13 members corresponded to the cargo-value observations exceeding the three-interquartile-range outlier threshold retained during preprocessing. Thus, the pronounced separation of Cluster 2 reflects the presence of an extreme high-value cargo group within the selected variables and should not be interpreted as evidence of an independently established freight-market category. Previous research has documented heterogeneity in freight travel-time valuations across shipment, transport, and decision-maker characteristics (Tao and Zhu 2020; Binsuwadan et al. 2022). However, these studies do not establish that Cluster 2's cargo characteristics caused its higher stated BCIB WTP. Given its small membership and dependence on the retained extreme cargo values, Cluster 2 is best interpreted as a specialized exploratory subgroup within the analyzed sample.

Cluster 3 – Long-Haul High-Cost Heavy-Freight Operators. Cluster 3 was the largest segment and was characterized by the longest mean HGV route distance (250.01 km) and reported travel time (6.61 h), as well as the highest mean toll cost (PHP 1,058.02), fuel cost (PHP 4,562.50), and cargo weight (27.64 t). Five- and six-axle vehicles were comparatively prominent, particularly six-axle truck–trailer combinations. Related Philippine freight research conducted within the same broader study context found that truck characteristics, payload, and load-management conditions were associated with freight fuel efficiency and operating performance (Vallejos and Fillone 2026). That earlier analysis provides related operational context rather than independent validation of the present cluster solution. Despite Cluster 3's substantially higher transport-cost exposure, its mean direct BCIB WTP of PHP 1,123.04 was similar to the PHP 1,102.60 observed for Cluster 1. For long-haul heavy-freight movements, the attractiveness of a new tolled connection would depend on whether the additional charge is offset by sufficient operational benefits.

Overall, the three profiles demonstrate heterogeneity not only in route distance and expenditure but also in cargo, vehicle, and organizational characteristics. The Kruskal–Wallis tests indicated statistically significant differences among the clusters for all seven clustering variables ($p < 0.001$). The largest effect sizes were observed for HGV route distance ($\varepsilon^2 = 0.565$) and reported travel time ($\varepsilon^2 = 0.491$), followed by toll cost ($\varepsilon^2 = 0.290$), fuel cost ($\varepsilon^2 = 0.151$), cargo value ($\varepsilon^2 = 0.131$), cargo weight ($\varepsilon^2 = 0.053$), and direct BCIB WTP ($\varepsilon^2 = 0.047$). Thus, route distance and travel time exhibited the largest differences across the resulting cluster profiles. Because these seven variables were used to construct the clusters, the statistical comparisons are descriptive and should not be interpreted as independent validation of the partition or as evidence of causal relationships. The Kruskal–Wallis results and Holm-adjusted pairwise comparisons are presented in Table 4.

Pairwise comparisons further clarified the segment profiles. Clusters 1 and 2 did not differ significantly in toll cost ($p = 0.573$), fuel cost ($p = 0.724$), or cargo weight ($p = 0.531$), but differed significantly in route distance, travel time, cargo value, and direct BCIB WTP. Clusters 1 and 3 differed significantly in route distance, travel time, toll cost, fuel cost, cargo weight, and cargo value, whereas their direct BCIB WTP distributions did not differ significantly ($p = 0.655$). Cluster 2 differed significantly from Cluster 3 on all seven clustering variables. The nonsignificant WTP comparison between Clusters 1 and 3 is noteworthy because Cluster 3 had greater average route distance, travel time, toll expenditure, fuel expenditure, and cargo weight, yet their mean stated maximum BCIB toll amounts were similar (PHP 1,102.60 and PHP 1,123.04, respectively). This finding suggests that higher current operating-cost exposure does not necessarily correspond to higher direct BCIB WTP within the observed sample. However, a nonsignificant result should not be interpreted as statistical equivalence, and these comparisons remain descriptive because direct BCIB WTP was included among the variables used to construct the clusters.

External operational, commodity, and organizational profiles

External profiling showed that the clusters differed in several characteristics that were not used to construct the K-means partition. Respondent category showed a negligible association with cluster membership ($p = 0.986$, Cramér's $V = 0.020$), indicating that the segmentation did not simply reproduce the proportions of respondent categories in the sample. At the unadjusted 0.05 level, associations were observed for commodity type ($V = 0.225$), hazardous cargo ($V = 0.293$), truckload type ($V = 0.164$), truck axle count ($V = 0.306$), truck configuration ($V = 0.324$), truck ownership ($V = 0.146$), and route decision-maker ($V = 0.252$). In contrast, perishable/time-sensitive cargo was not significantly associated with cluster membership ($p = 0.065$, $V = 0.124$).

Temperature-controlled status was not significantly associated with cluster membership ($p = 1.000$, $V = 0.029$). Among the significant associations, truck configuration and axle count had the largest Cramér's V values, followed by hazardous cargo, route decision-maker, commodity type, truckload type, and truck ownership. The categorical association results are summarized in Table 5.

Table 5: Categorical associations with final cluster membership

Characteristic	Chi-square	Permutation p	Cramér's V
Respondent category	0.299	0.986	0.020
Commodity type	36.336	0.006	0.225
Hazardous cargo	30.817	< 0.001	0.293
Temperature controlled	0.304	1.000	0.029

Perishable/time-sensitive	5.522	0.065	0.124
Truckload type	9.596	0.008	0.164
Truck axles	67.012	< 0.001	0.306
Truck configuration	75.193	0.001	0.324
Truck ownership	7.594	0.025	0.146
Route decision-maker	45.537	0.001	0.252

Commodity composition differed notably across the clusters. Cluster 1 was heterogeneous, with manufactured items (33.1%) and petroleum products (25.3%) as its largest commodity groups. Cluster 2 was strongly concentrated in petroleum products (84.6%), with manufactured items accounting for the remaining 15.4%. Cluster 3 was likewise heterogeneous, although manufactured items accounted for the largest share (42.9%), followed by petroleum products (25.7%). Hazardous cargo accounted for 27.9% of Cluster 1 and 27.7% of Cluster 3 but 100% of Cluster 2. Full-truckload operations represented 77.3%, 100.0%, and 67.0% of Clusters 1, 2, and 3, respectively. Company-owned trucks predominated throughout the sample, comprising 92.9% of Cluster 1, 100.0% of Cluster 2, and 98.4% of Cluster 3.

Route-decision authority showed a clearer distinction than respondent category. Drivers made 78.6% of the route decisions in Cluster 1 and 68.1% in Cluster 3. By contrast, no route decisions in Cluster 2 were driver-directed; 84.6% were made by the shipper/company owner and 15.4% by the client. The shipper/company owner was reported as the toll payer for all respondents, so toll-payer variation could not be subjected to an association test. These results emphasize the distinction among the survey respondent, route decision-maker, and toll payer. Prior freight-routing research has likewise shown that routing authority may vary with employment arrangements and that responsibility for fuel and toll expenditures is relevant to route-choice behavior (Sun et al. 2013). A driver may therefore select a route without personally bearing the toll expenditure. Related research comparing company drivers and owner-operators also highlights the importance of organizational context when evaluating truck-route preferences under different travel-time, reliability, and safety conditions (Kim and Arroyo Turcios 2023). Figure 3 summarizes selected external operational differences across the three clusters.

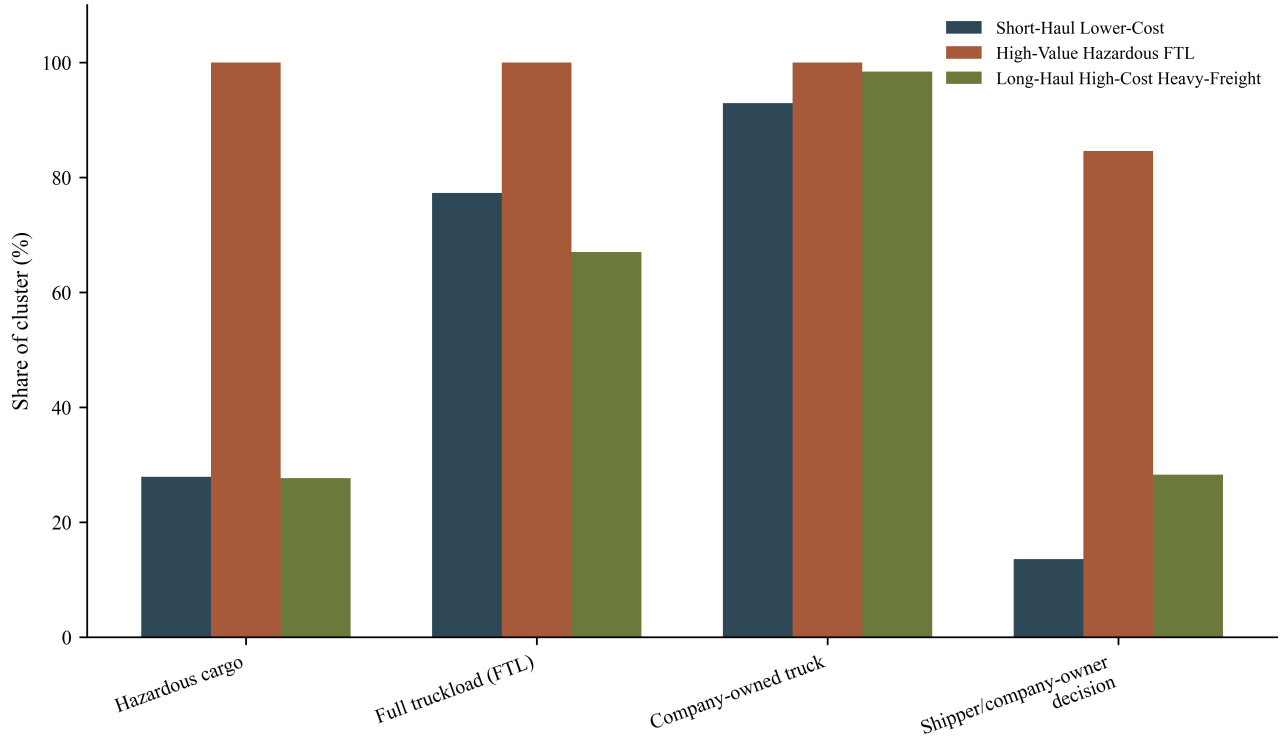


Figure 3: Operational characteristics of the three freight clusters.

PCA visualization and silhouette structure

The first two principal components explained 53.29% of the total variance in the seven standardized clustering variables, with PC1 accounting for 33.67% and PC2 accounting for 19.62%. The PCA visualization showed that Cluster 2 occupied a relatively distinct region of the two-dimensional feature space, whereas Clusters 1 and 3 exhibited greater overlap. Figure 4 presents the principal component visualization of the final three-cluster solution, with shaded regions representing 95% covariance ellipses and X markers indicating cluster centroids. Because the two principal components captured only slightly more than half of the total variance, the visualization should be interpreted as a partial representation of the seven-dimensional cluster structure rather than definitive evidence of separation.

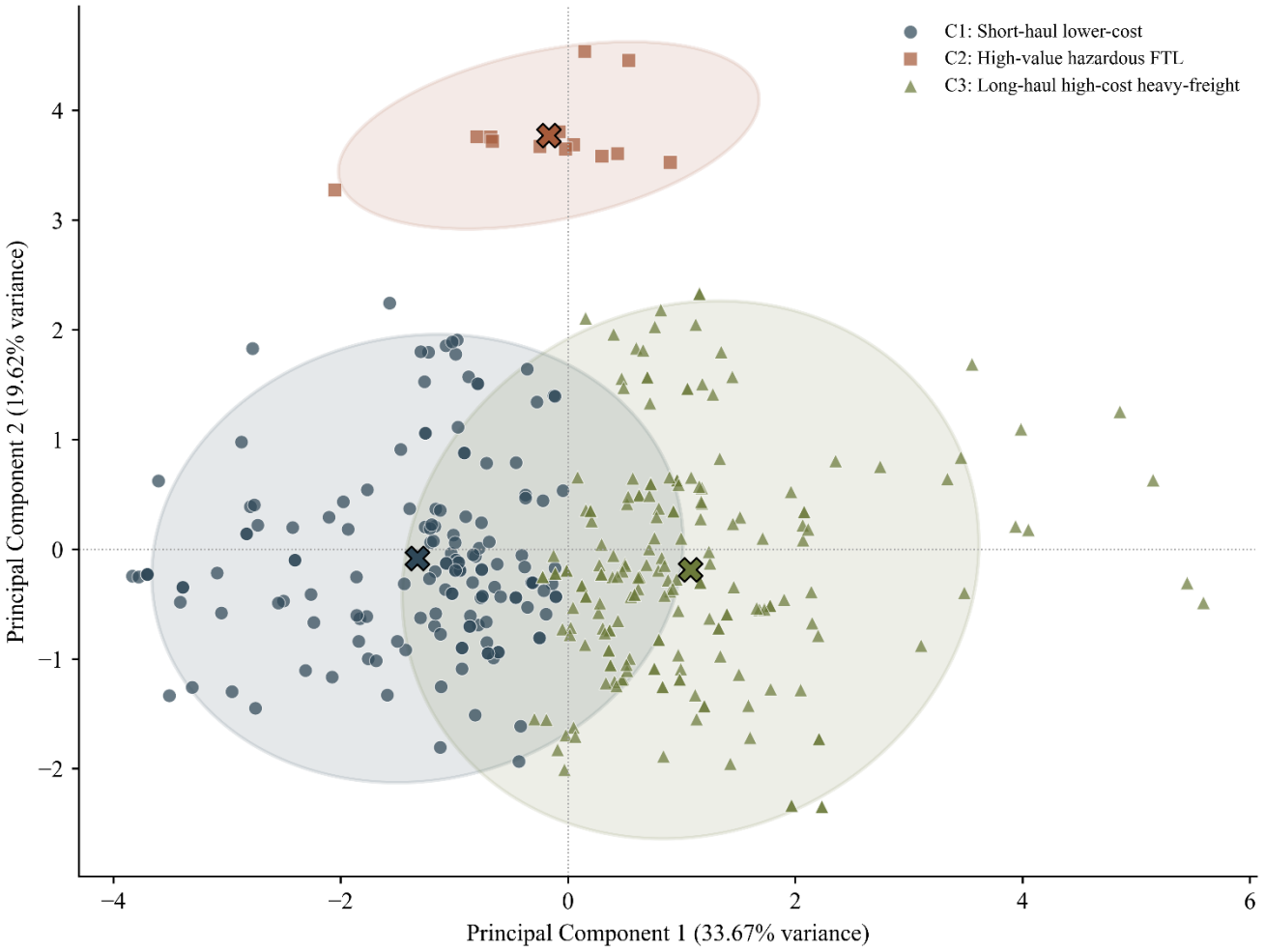


Figure 4: Principal component visualization of the final three-cluster solution.

Cluster-level silhouette results provide a more detailed assessment of cluster separation. Mean silhouette coefficients were 0.256 for Cluster 1, 0.702 for Cluster 2, and 0.153 for Cluster 3. Cluster 2 exhibited the strongest separation, whereas Cluster 3 showed the greatest overlap with neighboring observations. Fifteen respondents had negative silhouette values, all belonging to Cluster 3. These represented 4.19% of the full sample and 7.9% of Cluster 3. Silhouette values near zero indicate observations positioned between groups, whereas negative values indicate that an observation is, on average, more similar to another cluster than to its assigned cluster (Rousseeuw 1987). The overall silhouette coefficient of 0.218 indicates limited separation, particularly between the two larger segments. Nevertheless, the high initialization stability and generally strong subsampling agreement support the reproducibility of the selected K-means partition. Taken together, these findings provide an interpretable exploratory basis for examining heterogeneity in freight operations while recognizing overlap among the identified segments. Figure 5 presents the distribution of individual silhouette values across the clusters, with diamond markers indicating cluster means.

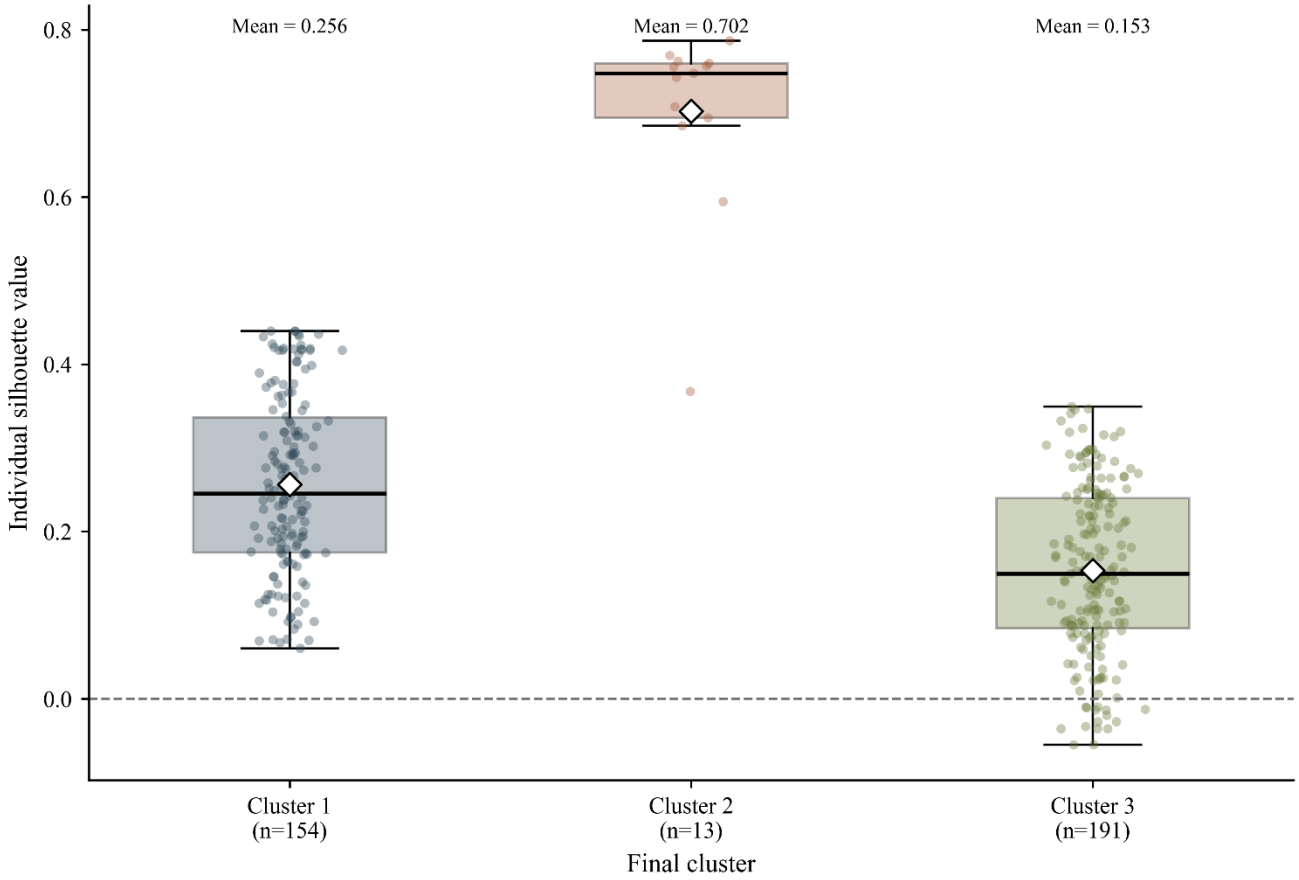


Figure 5: Distribution of individual silhouette values for the final three-cluster solution.

Direct BCIB WTP and planning implications

Direct stated BCIB WTP was included among the seven clustering variables and provides a descriptive indication of differences in stated maximum toll amounts across the identified freight segments. Mean direct WTP was PHP 1,102.60 for Cluster 1, PHP 1,538.46 for Cluster 2, and PHP 1,123.04 for Cluster 3. Cluster 2 therefore stated the highest mean maximum toll amount, whereas Clusters 1 and 3 had similar values despite substantial differences in route distance, travel time, existing toll expenditure, fuel expenditure, and cargo weight. These amounts may be considered in relation to the financial assumptions used in the BCIB project appraisal. For operations commencing in 2030, the appraisal assumes PHP 14.20 per vehicle-kilometer for Class 2 vehicles, including two-axle trucks, and PHP 21.30 per vehicle-kilometer for Class 3 vehicles, including trailers and trucks with three or more axles (AIIB 2024). Applied to the approximately 32.15-km bridge length, these assumptions correspond to approximately PHP 457 for Class 2 and PHP 685 for Class 3 over the full crossing. The appraisal further assumes toll escalation over the operating period. These figures are project-appraisal assumptions rather than a final approved toll schedule. The mean direct WTP of each cluster exceeds these base appraisal amounts. This comparison should nevertheless be interpreted cautiously. The direct WTP variable represents a stated maximum toll under the hypothetical BCIB-use context presented in the survey; it does not establish that respondents will actually use the bridge under future operating conditions. Actual use would depend on the toll eventually implemented, realized travel benefits, vehicle classification, competing routes, congestion, fuel prices, and other operational conditions.

The project appraisal also underscores the relevance of toll levels to projected demand. The AIIB appraisal reports a 22% reduction in projected traffic under a sensitivity scenario in which tolls were introduced for operation and maintenance cost recovery, while the project remained economically viable under that scenario (AIIB 2024). This project-level projection highlights the potential sensitivity of traffic demand to toll charges but does not represent an observed freight-specific response. Direct BCIB WTP must also be distinguished from the value of freight travel time savings (VFTTS). VFTTS represents the marginal rate of substitution between travel time and monetary cost and is generally derived from behavioral choice models rather than from a single stated maximum toll amount (Binsuwadan et al. 2022). Accordingly, the direct BCIB WTP values in this study should not be interpreted as formal VFTTS estimates. The comparison between Clusters 1 and 3 is noteworthy because Cluster 3 had substantially higher mean current operating expenditures, yet the two clusters reported similar mean direct BCIB WTP values, with no statistically significant difference in their WTP distributions (Holm-adjusted $p = 0.655$). This descriptive finding indicates that differences in current operating-cost exposure were not accompanied by a corresponding statistically detectable difference in stated BCIB WTP between these two segments. However, the comparison does not establish statistical equivalence or an independent relationship between operating costs and WTP.

For planning purposes, the findings suggest that freight users relevant to the BCIB should not be represented solely by a single aggregate truck profile. Cluster 1 represents shorter and lower-cost movements; Cluster 2 represents a specialized high-value hazardous FTL profile with organizational route control; and Cluster 3 represents longer, heavier, and more cost-exposed movements. Philippine evidence similarly indicates an association between road-freight costs and road-infrastructure conditions and emphasizes the role of expressway development in freight competitiveness (Suarez et al. 2022). These profiles highlight operational and organizational characteristics that may be relevant to differences in responses to future toll and corridor conditions.

However, the current clustering analysis does not estimate toll elasticity, fuel-price elasticity, diversion rates, or BCIB adoption probabilities, and such behavioral responses should not be inferred directly from cluster membership. The identified segments can nevertheless provide a basis for subsequent route-choice research. A recent large-truck study, for example, combined trajectory clustering with a conditional logit model to evaluate route-choice alternatives and heterogeneity (Ma et al. 2025). The present clusters should not, however, be described as latent classes because they were obtained independently from operational, shipment, cost, and stated WTP characteristics rather than jointly estimated with route-choice probabilities.

Robustness and limitations

Several methodological features support the reproducibility and interpretability of the retained exploratory segmentation. All 358 validated respondents had complete observations for the seven clustering variables and were included in the analysis. Extreme observations were reviewed against the underlying survey records and retained when considered valid. The number of clusters was assessed using complementary internal-validation criteria, while partition stability was examined through repeated centroid initialization and subsampling. The initialization analysis yielded identical partitions across 100 random-seed runs (ARI = 1.000), while the subsampling assessment demonstrated generally high agreement (mean ARI = 0.931). Together with the observed operational and organizational differences among the cluster profiles, these findings support the use of the three-cluster solution as a reproducible and interpretable exploratory segmentation of freight operations in the study area, without implying sharply delineated underlying categories.

Several considerations define the scope of the findings. K-means is a centroid-based clustering method that minimizes within-cluster squared Euclidean distances, and the resulting partition depends on the selected variables, their representation, the specified number of clusters, and the underlying data structure (Jain 2010). Because purposive sampling was employed, the observed cluster proportions should not be interpreted as population prevalence estimates. This consideration is particularly relevant to Cluster 2, which contained only 13 observations. In addition, several operating-cost and shipment variables were respondent-reported and may contain reporting error despite the data-cleaning and validation procedures. Direct BCIB WTP was obtained from a hypothetical bridge-use question and should not be equated with observed future toll-payment or route-use behavior. The study is also cross-sectional and reflects the freight-operating conditions represented in the survey. It therefore cannot determine how individual freight operators will alter their routes in response to the eventual BCIB toll schedule, future fuel prices, congestion conditions, or realized travel-time savings. Accordingly, the findings should be interpreted as an exploratory segmentation of freight operations relevant to BCIB planning rather than as a prediction of future bridge use. The principal contribution of the segmentation is to identify operational, shipment, vehicle, cost, and organizational heterogeneity that may be relevant when evaluating potential freight users of a major new tolled connection.

CONCLUSION

This study identified three freight-operation segments from a validated sample of 358 respondents in Bataan, Philippines, using K-means clustering on seven standardized trip, operating-cost, shipment, and direct stated BCIB WTP variables. The retained solution consisted of Short-Haul Lower-Cost Freight Operators (43.0%), High-Value Hazardous FTL Freight Operators (3.6%), and Long-Haul High-Cost Heavy-Freight Operators (53.4%). Multiple internal-validation and stability assessments supported retention of this parsimonious three-cluster solution for exploratory analysis, although some overlap remained between the two larger segments.

The findings show that freight heterogeneity in the Bataan sample extends beyond route distance and transport expenditure. Exploratory external profiling identified associations at the unadjusted $p < 0.05$ level between cluster membership and commodity type, hazardous cargo, truckload type, axle count, truck configuration, truck ownership, and route-decision authority. In contrast, respondent category, temperature-controlled status, and perishable/time-sensitive cargo were not significantly associated with cluster membership. The specialized high-value segment was the most clearly separated, with all 13 observations involving hazardous cargo, full-truckload operations, and company-owned trucks, and it exhibited the highest mean direct BCIB WTP. The long-haul segment had the greatest mean route distance, travel time, toll expenditure, fuel expenditure, and cargo weight, yet no statistically significant difference in direct BCIB WTP was detected between the long-haul and shorter-haul segments. This finding highlights the importance of considering multiple operational and shipment characteristics when examining stated willingness to pay for a proposed tolled connection. For BCIB planning, the results suggest that potential freight users should not be represented solely by a single aggregate truck profile. Differences in shipment characteristics, vehicle configuration, existing transport costs, and route-decision authority provide relevant dimensions for examining freight-user heterogeneity. The identified segments therefore provide an exploratory basis for considering differentiated freight-operation profiles in corridor and toll planning. The clusters should not be interpreted as predictions of future BCIB use. Direct BCIB WTP was obtained from a hypothetical bridge-use question, and the analysis does not estimate toll elasticity, diversion rates, adoption probabilities, or formal value of freight travel-time savings. Future research may extend the analysis through behavioral route-choice models to examine whether freight operations with different characteristics respond differently to toll levels, travel-time savings, reliability, and operating costs.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

CONTRIBUTIONS OF INDIVIDUAL AUTHORS

M.M.V.: Conceptualization, Methodology, Investigation, Formal analysis, Visualization, Writing – original draft, Writing – review and editing. A.M.F.: Supervision, Writing – review and editing.

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