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QFD Application in Cross-Border E-Commerce Third-Party Logistics Provider Selection

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Abstract

This study aims to demonstrate the potential use of Quality Function Deployment (QFD) in selecting a cross-border Third Party Logistics (3PL) provider. Our approach involves extending conventional QFD with Bayesian Networks (BN) with ranked nodes and a multi-criteria decision analysis method such as Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). This way, the cross-border 3PL provider selection process will incorporate the voice of overseas customers and expert knowledge. Cooperating with lovely wholesale, a cross-border E-commerce wholesaler of women's clothing, we record the Voice of Customers (VOC) through a survey, develop decision criteria, compute their relative importance weights, and build a correlation matrix using the House of Quality (HOQ). A causal nexus graph is formed based on the correlation analysis. We use a parameterization of BN called Ranked Nodes, which lets experts contribute their expertise in natural language phrases. BN produces the decision matrix, while the relative importance weights are used as criteria weights in ranking with TOPSIS. A successfully ranked list of alternatives confirms that the methodology developed in this work may aid in selecting the most appropriate cross-border 3PL provider, considering the voice of the customer.

Keywords: Bayesian networks, Cross-border third party logistics provider, House of quality, Quality function deployment, Ranked nodes, Voice of customer.

1 | Introduction

In 2009 China became Africa's largest bilateral trading partner, surpassing the United States. In contrast to its primary raw resource exports, Africa increasingly relies on China as a supplier of manufactured goods, including textiles, equipment, and electronics. Residents of rural Africa can access commodities they would otherwise lack due to the high cost of production associated with various products. As a result, Africa's import

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and export patterns have shifted, and the continent's growth has accelerated. Secure and dependable international logistics and transport for online purchases are essential as international trade continues [1], [2]. It is critical to ensuring success in international online trading.

China's reopening post-COVID-19 and Beijing's drive to increase imports from Africa contributed to a record US$282 billion in trade between China and Africa in 2022. China's exports to the African continent will be US$164.49 billion in 2022, with an annual growth of 11.2 % compared to 2021 [3]. At the same time, imports from Africa increased at a comparable pace, reaching US$117.51 billion. It is a positive trend after the disastrous effects of the Covid-19 outbreak on trade in 2020.

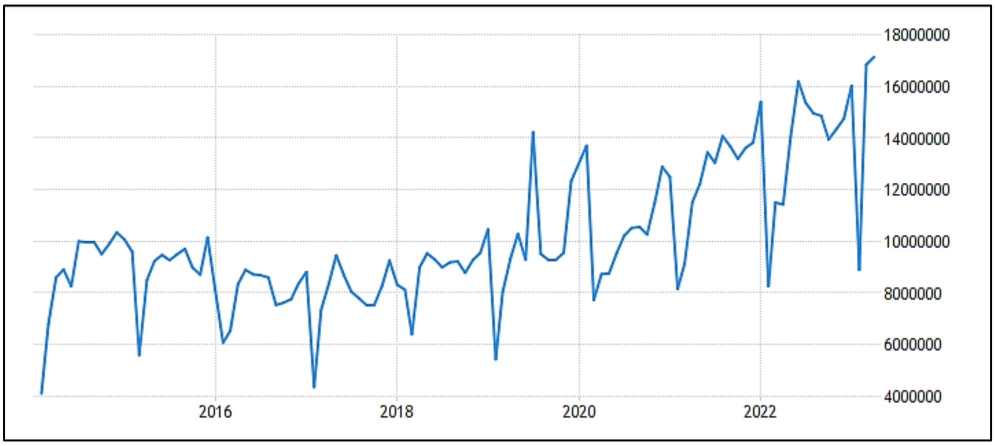


Fig. 1. China's exports to Africa trend over 10 years.

Since the launch of China's one belt one road program in 2013, China's businesses have been more active on the African continent, see *Fig. 1*. Their goods are often tailored specifically to the requirements of their African market. The growth of business-to-consumer cross-border online trade and the structural progress in China's foreign trade industry go hand in hand. The thriving cross-border online trade sector is driving increasing demand for logistics and transportation services. Essential elements in international logistics and transportation systems now include dependability, controllability, security, stability, low cost, information technology, and intelligence [4].

There is insufficient current knowledge on transportation and logistics between China and Africa. The impact of the Chinese government and businesses on Africa's progress and the growth of cross-border online trade between China and Africa are the primary topics of current studies.

E-commerce traders need to involve overseas customers in selecting cross-border Third Party Logistics (3PL) providers. In cases where buyers and sellers have varying logistical needs, it can be not easy to assess new logistics service providers' performance across all criteria. In such a situation, decision-makers can benefit from the Voice of Customers (VOC) and logistics experts' knowledge and insight. The trader can get relevant data about factors, such as cost, by conducting market research through the Quality Function Deployment (QFD) process. The findings can be used to create informed opinions about the value of factors such as real-time tracking and logistical updates to the buyer. A buyer may be interested in knowing the courier's capabilities in product quality, timely delivery, and others. However, decision-making in modern markets is more challenging than ever due to developments in alternatives, objectives, and ecological conditions that have occurred in tandem with technological advancements [5]. To that end, we present an approach that incorporates the VOC, the expertise of cross-border E-commerce stakeholders, and tools that aid in systematic decision-making. We are confident the methodology proposed in this paper is crucial for making sound decisions even with limited information.

In conclusion, as international online trade grows in importance, so do the issues surrounding international online supply chains. Hot trends in the evolution of cross-border online logistics logistics transportation include reliability, safety, cost, and other crucial factors to traders and customers. However, selecting an appropriate logistics partner with minimal trade-offs among the factors to consider is a pressing issue.

Here's how the remainder of the paper is laid out. The works that are relevant to this discussion will be shown in Section 2. The fundamentals of the methodology are described in Section 3. The proposed systematic approach is presented with a case study in Section 4. Section 5 provides a conclusion and future scope.

2 | Literature Review

2.1 | Review of Cross-Border Online Trade Research

To better understand the factors that influence cross-border online trade decisions in the European Union's unified digital market, [6] looked at the relevance of physical distance to E-commerce and analyzed the beneficial function of policymakers. Gomez et al. [7] evaluated and contrasted the elements that affect and the difficulties associated with international commerce in different formats, such as online and offline. Liang et al. [8] Talked about encouraging the building of overseas warehouses and fairly selecting the cross-border logistics method to raise the service quality in cross-border online trade. To accelerate the growth of international E-commerce in Fujian, China, [9] proposed remedies from the perspectives of assistance from local authorities and encouraging the establishment of credit systems, among others.

2.2 | Review of Cross-Border Online Trade Supply Chain Optimization

Supply chain management coordination and efficiency measures like integrating China's supply chain procurement system, building cross-border superior E-commerce, reliance on big data application, and increasing supply chain management capacities are proposed by [10] in light of the challenges associated with international transportation of goods. Demand price elasticity was initially proposed by [11] and is affected by a wide range of logistical considerations, including planning and scheduling of production, inventory handling, and shipping constraints. [10] suggested ways of tightening security in global supply chains, hence increasing the network's survivability.[12] researched the elements that affect the effectiveness of international online commerce supply chains and developed the driving parameter framework. An optimal control method for a multilayer return supply chain was presented by [13] using a supply chain model that integrates optimization techniques. The process for optimizing a supply chain with several products was presented by [14]. Using a universal graphical representation, these formulas capture the interdependencies of goods, technology, and transportation routes.

2.3 | Review of Cross-Border Online Trade Logistics Mode Selection Evaluation

To choose suppliers, [15] suggested a fuzzy decision approach. Within modularization and delay, [16] presented theoretical foundations for assessing various supply chain topologies. To achieve the optimum selection of international logistics providers, [17] suggested a goal-oriented fuzzy programming approach incorporating pricing and output performance metrics. [18] investigated the dependability of a sophisticated logistics network. When it comes to running a successful supply chain business, demand forecasting is crucial. After accounting for potential outliers in the planning phase, [19] accurately forecasted the demand for international E-commerce logistics. To better match international demand with local suppliers based on the satisfaction of multiple stakeholders, [20] adapted the correlative method to the cross-border online trading environment. In their research, [21] examined the elements influencing online shoppers' decisions to engage in cross-border online trade. They gathered customer data worldwide and viewed it through the lens of psychological distance, commitment, and trust.

2.4 | Review of Factors That Stimulate China-African Cross-Border E-Commerce

Many people believe that Africa can be said to be the most promising E-commerce market in the world. The rapid expansion of the African E-commerce market has attracted the attention of investors and business people worldwide [22]. E-commerce between China and the African continent may increase as a result. The following reasons have contributed to the growth of online trade between China and Africa.

Consistent growth of internet usage: E-commerce in Africa will benefit from the current surge in Internet penetration in the region. As of January 2022, Morocco had the highest penetration rate in Africa, reaching 84.1%. Seychelles ranks second with a proportion of 79%, followed by Egypt with approximately 72%. South Africa ranks fourth with 68.2%. Tunisia ranked fifth with a score of 66.7% [23].

Rise in mobile communication: due to mobile payment systems, global E-commerce is thriving, and purchasing power in remote areas is increasing. According to [24], sub-Saharan Africa had a growth rate of 12% for 30-day active mobile accounts in 2018. The number of mobile phone users in sub–Saharan Africa is expected to increase from 456 million at the end of 2018 to over 600 million by 2025 [24].

Promising E-commerce potential: overall, the African market is not yet mature, and it is challenging to meet the needs of its customers. Africa is still in the early stages of industrialization, with low manufacturing output, low proportion of manufacturing employment, and low export volume [25]. Compared to other emerging regions, Sub-Saharan Africa had one of the lowest growths in manufacturing value-added between 1990 and 2011. Especially in sub–saharan African countries, uneven industrial growth, and weak industrial foundations have led to a shortage of locally manufactured goods, stagnant retail development, and a scarcity of traditional stores. In that case, products manufactured in other countries have a large customer base.

The surge in international online trade has changed the conventional trade value chain. In Africa, the Chinese electronic product market is flooded with low-priced products. The increasing supply of Chinese products in Africa has increased consumer satisfaction across all economic categories.

Favorable policies: to encourage and control the rapid expansion of the online market on the African continent, some African countries have passed comprehensive E-commerce laws and regulations. In addition 2019, 44 African countries approved the African free trade area agreement, forming the world's largest single market. When the African Trade Area was established and the African continent digitized, E-commerce became a focal point of growth.

3 | Methodology

This paper focuses on selecting cross-border 3PL providers incorporating customer needs and technical requirements. A methodology comprising three approaches is developed to achieve this goal: QFD for construction of HOQ, elicitation of the decision matrix using BN with ranked nodes, and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). With a stack for ranking alternatives. In general, HOQ provides a correlation matrix based on the connectivity of the decision criteria, and relative importance weights are calculated from the computation of the relationship matrix and relative weights.

The correlation matrix yields a causal nexus as input for BN. Ranked nodes are used to develop qualitative estimates in BN. BN with ranked nodes builds a decision matrix for TOPSIS. Relative importance weights from HOQ are used as weights of criteria in TOPSIS. The framework of methodology is illustrated in *Fig. 2*.

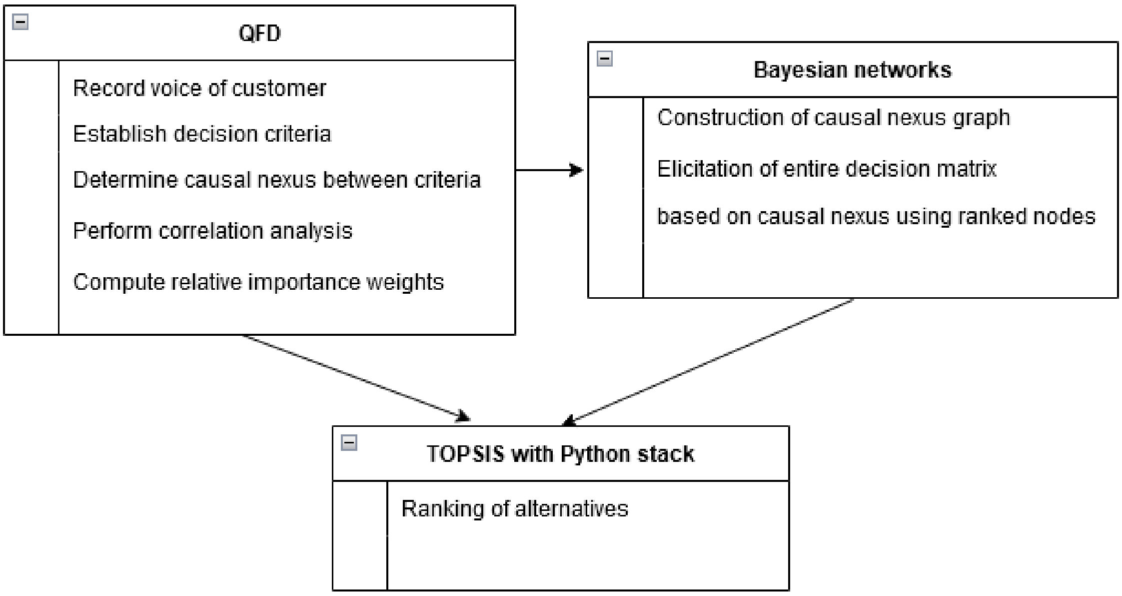


Fig. 2. Proposed methodology.

3.1 | Construction of House of Quality

QFD is used to translate the voice of the customer into technical requirements that the service provider must have to meet customers' needs. Technical requirements are hereby referred to as decision criteria.

This structured understanding is summarized in House of Quality (HOQ). In this study, HOQ captures customer needs, technical requirements, relationship matrix of customer needs and technical requirements, relative importance weights, and correlation matrix of decision criteria. The HOQ constructed in this study takes the model provided in *Fig. 3*.

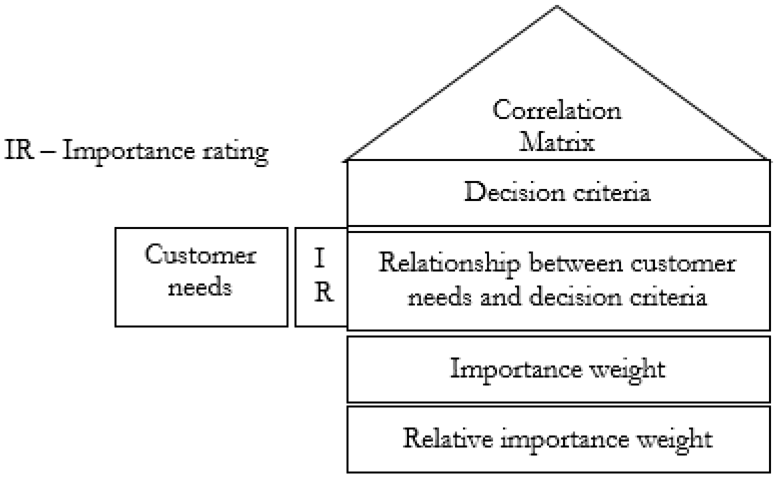


Fig. 3. Model of HOQ.

3.1.1 | Recording customer needs WHATs

The first stage is to develop a list of needs that fully reflects the customer's perspective. A questionnaire was used for this purpose. Customers assigned the list with importance ratings from 1 to 10, with 10 indicating the most important and 1 indicating the least important. The averages of their responses were computed and refined into *Table 1*.

3.1.2 | Developing the decision criteria

The HOQ provides a framework to meet or exceed customer needs. After recording customer needs, the project team must identify decision criteria that will affect the identified customer needs. The decision criteria were listed on the second level of the HOQ. This process relies on the collective expert knowledge of the project team. Using consultations and consensus, the decision criteria were generated. These criteria are listed as shown in *Tabel 2*.

3.1.3 | Build a relationship matrix of the customer needs and decision criteria

This task of HOQ examines the connections between customer needs and decision criteria. One customer might affect several decision criteria and vice versa. The project team fills the center of HOQ. The relationship matrix shows the degree of influence between customer needs and decision criteria. In this paper, the degree of influence is defined by the following numbers: 5 represents strong influence, 3 represents medium influence, 1 represents weak influence, and 0 represents no influence.

3.1.4 | Calculation of importance weights and relative importance weights

Weights are an essential output in conventional QFD. They help in determining the development direction. This paper uses relative importance weights as criteria for ranking with TOPSIS.

Importance weights and relative importance weights are calculated using the following formula:

$$a_j = \sum_{i=1}^{n} R_{ij} c_i, \; j = 1, \ldots, m. \tag{1}$$

Where R_{ij} is the relationship coefficient of the relationship matrix $(i = 1, \ldots n, j = 1, \ldots, m)$, c_i is the importance rating of the customer needs $(i = 1, \ldots, n)$, m is the number of decision criteria, and n is the number of customer needs in the HOQ.

The relative importance weight of jth the criterion is calculated by dividing the summation of importance weights by its importance weight multiplied by 100% to give a percentage.

3.1.5 | Construction of correlation matrix of decision criteria

The correlation matrix is the interaction of decision criteria. The matrix assumes the shape of a pitched roof at the top of HOQ. It determines which decision criteria support each other directly and which ones do not have direct support for each other. In this paper, the symbols "+" and "-" show direct and lack direct connectivity. The project team establishes whether there is a direct relationship between decision criteria. An appropriate symbol is entered into the corresponding cell of the pair of decision criteria. This paper uses the correlation matrix to generate a causal nexus graph that is then deployed in Bayesian networks.

3.2 | Using Bayesian Networks to Construct Causal Nexus Graph and Generate Decision Matrix

3.2.1 | Constructing causal nexus with BN

The graph is built based on criteria connectivity established in the correlation matrix. A unidirectional arrow is used to indicate the parent-child relationship amongst the nodes. That is the arrow points to the child. BN graphs show a systematic causal relationship and allow flexibility when the existing expert knowledge needs to be updated. In this paper, letters M to V represent node nodes of decision criteria, as shown in *Fig. 6*.

3.2.2.Generating decision matrix with BN

When new evidence is collected, BNs update all networks by recalculating the conventional probability. Nodes in BNs stand in for decision criteria, while arcs show their relationship regarding cause and effect. The Node Probability Table (NPT) for each node contains the parameters of the node's conditional probability distribution [26]. In terms of visually representing the causal nexus between decision criteria, BNs are also used. BNs systematically and probabilistically examine how different criteria affect each other. BNs adapt to new information and provide revised findings due to their ability to incorporate new information.

3.2.3 | Using ranked nodes to describe nodes in BN

The BN feature, ranked nodes, describes nodes in a Bayesian network arranged according to specific criteria [27]. This study uses ranked nodes with the weighted mean function.

Suppose M, N, O, and P are nodes in a Bayesian network. We may arrange the nodes in a hierarchy, with node P at the top, followed by nodes M, N, and O, depending on their significance or value for the represented issue. In this BN example, alternative P depends on alternatives M, N, and O; each node has five possible states. We need to collect probability estimates to calculate the NPT of O, assuming that RNs are not used. This is difficult when computed manually and is likely to lead to misinterpretation. Using ranked nodes might benefit from modeling complex systems and making forecasts or assessments based on vast data. In the above example, using ranked nodes with a Weighted Mean function and five BN states would simplify the work. WMEAN determines the child node's midpoint depending on the parent node's values.

3.3 | Ranking of Alternatives with TOPSIS in Python Stack

TOPSIS uses a distance-based MCDM approach [28]. That is, the more closely it approaches the ideal, the better. In this study, we integrate TOPSIS with the scientific Python stack in jupyter notebook. This is because our case study has ten decision criteria and six alternatives. Large amounts of data would take a long time to compute manually. TOPSIS with Python stack in Jupyter Notebook starts by importing the required libraries: Pandas and Numpy as pd and np, respectively. In this case, the decision matrix elicited from the BN software and the weights of criteria computed in HOQ are imported. It is followed by inputting alternative names and creating a data frame. The data frame creates a table form of the matrix with alternatives and attributes.

The subsequent significant steps are shown in *Fig. 4*.

I. Compute normalized decision matrix. This process flattens the dimensionality of attributes so they may be compared objectively across criteria. Since different criteria are often scored using other units, the evaluation matrix X's scores must be translated to a normalized scale.

II. Compute the weighted normalized decision matrix.

III. Compute positive and negative ideals.

IV. Compute the separation measures.

V. Compute the relative similarity of alternatives to the positive ideal.

VI. Rank alternatives in descending order.

```
## STEP 1 - Normalization
Data_norm = Data/np.sqrt(np.power(Data,2).sum(axis=0))
```

```
Data/np.sqrt(np.power(Data,2).sum(axis=0))
```

...

```
## STEP 2 - Weighted normalized ratings
Data_norm_w = Data_norm*w
Data_norm_w
```

...

```
## STEP 3 - Identifying positive and negative ideals
positive_ideal = Data_norm_w.max()
negative_ideal = Data_norm_w.min()
```

Data_norm_w.min()

```
Data_norm_w.max()
```

...

```
## STEP 4 - Separation Measurements:
## Positive Ideal
SM_P = np.sqrt(np.power(Data_norm_w-positive_ideal,2).sum(axis=1))
## Negative Ideal
SM_N = np.sqrt(np.power(Data_norm_w-negative_ideal,2).sum(axis=1))
```

```
np.sqrt(np.power(Data_norm_w-positive_ideal,2).sum(axis=1))
```

...

```
## STEP 5 - Relative similarity of alternatives to the positive ideal
SM_N/(SM_N+SM_P)
```

Fig. 4. Steps of TOPSIS with Python stack.

3.4 | Contributions of the Proposed Methodology

I. The proposed approach incorporates relative importance weights considering voice of customer and expert knowledge in the selection process.

II. This methodology acknowledges the interdependencies between the decision criteria for making a choice and adjusts the network accordingly if there is a change in the criteria.

III. Unlike conventional QFD, correlation matrix forms part of the decision-making process.

IV. The probability of BN may be easily elicited using Ranked Nodes, which are based on qualitative inputs.

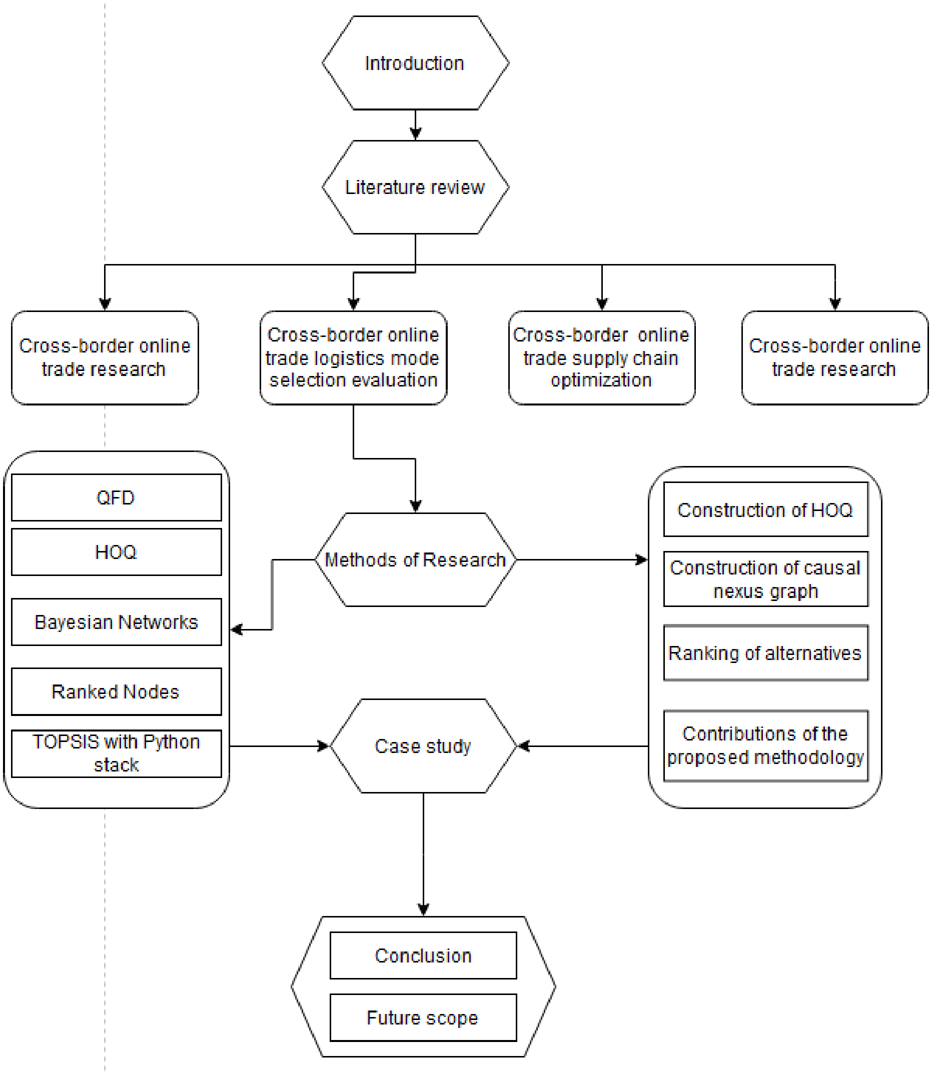
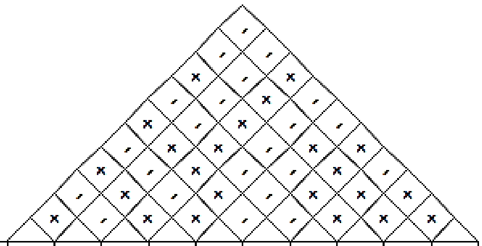


Fig. 5. Implementation flow chart of this study.

4 | Case Study

For research purposes, we collaborate with lovely wholesale, a clothing company with a warehouse in Guangzhou, China. It is safe to say the company's products are customized to meet customers' fashion and design desires in Africa, the United States, and around the world. The company has fulfilled 9,800 customer orders across Africa in the past three years. 58% of the orders were made in South Africa. We therefore decided to evaluate cross-border 3PL providers from Guangzhou, China, to Cape Town, South Africa. They are FedEx, DHL, TNT, Aramex, EMS, and UPS. The mode of transport considered in the research is air transport.

The mission is to rank the 3PL providers and select the best alternative for the company's South African market. QFD systematically incorporates BN with Ranked nodes and TOPSIS with Python with the stack. Based on the findings, we suggest how lovely wholesale should select a cross-border logistics partner based on customer needs and decision criteria. We coordinate with the company's customer relations department to survey sampled wholesale buyers based in Cape Town, South Africa. The sampled customers were selected based on their long business history with lovely wholesale, including occasionally changing their 3PL preference. We gave a quantitative and qualitative survey to the 20 sampled customers. The survey received responses from all the sampled wholesale customers.



Importance rating - IR	Decision criteria	M	N	O	P	Q	R	S	T	U	V
		Package processing speed	Cross-border air transport duration	Delivery time from local warehouse	Cost incurred by customer	Insurance of packages in transit	Real time tracking capability	Responding to customer concerns	Logistical updates to customers	Safety of package	Delivery to the right address
Customer needs	IR										
Short package processsing time	7	5	3	3	5	0	1	0	5	0	0
Convenient shipping time	9	5	5	5	5	0	1	3	3	0	1
Covenient last mile delivery	6	3	0	5	5	3	5	5	5	3	5
Affordable cost	8	3	1	5	5	5	3	0	0	1	0
Insurance for packages	7	0	3	5	3	5	0	1	0	5	3
Reliable real-time tracking	7	1	5	5	1	0	5	5	5	5	3
Timely response to concerns	8	0	0	1	0	3	5	5	3	5	1
Timely logistical updates	6	3	5	5	0	3	5	3	5	3	5
Safe delivery of package	9	0	0	5	3	5	3	1	3	5	5
Delivery to the right address	9	0	0	5	1	1	5	3	5	1	5
Importance weight		147	160	334	214	189	247	193	253	208	209
Relative importance weight		0.068	0.074	0.156	0.099	0.088	0.115	0.090	0.117	0.097	0.097

Fig. 6. The HOQ was constructed as shown in.

4.1 | Recording the Voice of the Customer

A list of features representing the customer's opinions was developed through discussions and consensus amongst the customer relations team of lovely wholesale. Customers rated the importance of each feature on a scale of 1 to 10. One represents "not important," while 10 represents "highly important." The data was refined, as shown in *Tabel 1*.

Tabel 1. Voice of customer.

Logistics Factor	Customer Needs (WHATs)	Index	Importance Rating
Transportation time	Short package processing time	A	7
	Convenient shipping time	B	9
	Convenient last-mile delivery	C	6
Transportation cost	Affordable cost	D	8
	Insurance for packages	E	7
Service level	Reliable real-time tracking	F	7
	Timely response to customer concerns	G	8
	Timely update customers	H	6
Reliability	Safe delivery of packages	I	9
	Delivery to the correct address	J	9

4.2 | Developing Decision Criteria

The next step is to develop a list of meaningful decision criteria that can quantify the performance of the company service. This QFD process involved the participation of all the project team members. Discussions and brainstorming were given ample time to develop the proper decision criteria. They were grouped as shown in *Table 2*.

Table 2. Decision criteria.

Logistics Factor	Decision Criteria (Hows)	Index
Transportation time	Package processing speed	M
	Cross-border air transport duration	N
	Delivery time from the local warehouse	O
Transportation cost	The cost incurred by the customer	P
	Insurance of packages in transit	Q
Service level	Real-time tracking capability	R
	Responding to customer concerns	S
	Logistical updates to customers	T
Reliability	Safety of package	U
	Delivery to the correct address	V

4.3 | Build a Relationship Matrix of the Customer Needs and Decision Criteria

The customer needs, and decision criteria relationship matrix is located at the center of HOQ. The strength of a relationship is determined by asking how the technical requirement in question is vital to meeting the respective customer's needs. Substantial responses were arrived at by consensus of the project team.

For example, starting with the first customer needs, the question is framed as, do you think "short package processing time in the warehouse" is relevant to "delivery time from local warehouse"? The response is "YES," with a "medium" degree. The degree of relevance is recorded as 3. The relationship matrix was completed following a similar trend. The project team's experience and complete knowledge were relevant to this exercise's success. The relationship matrix helps to understand the implications of changes in one technical requirement and another.

4.4 | Calculation of Importance Weights and Relative Importance Weights

In the relationship matrix table, each score is multiplied by the corresponding importance rating for the voice of the customer. In *Fig. 6*, for example, the cells representing "affordable cost" and "cost incurred by customer" have a product of 5*8= 40. In the same way, each customer need's importance rating is multiplied by the corresponding value in the relationship matrix. *Eq. (1)* was used to calculate the importance weights of each technical requirement. For the column "logistical updates to customers," this will be calculated as

$$(5\times7)+(3\times9)+(5\times6)+(0\times8)+(0\times7)+(5\times7)+(3\times8)+(5\times6)+(3\times9)+(5\times9)=253. \quad (2)$$

The importance weights of all decision criteria are calculated similarly. All importance weights were summarized as 2154 and used to calculate the relative importance weight of each technical requirement. Relative importance weights were used as weights of criteria in ranking the alternatives with TOPSIS.

4.5 | Correlation Matrix of Decision Criteria

The project team established the connectivity between various decision criteria. "+" and "-" symbols indicated direct and no direct relationships, respectively. The fully deployed correlation matrix is at the top of *Fig. 6*. To incorporate correlation matrix analysis into determining the causal nexus of decision criteria, BN with ranked nodes concept was incorporated into the methodology. The correlation matrix is not utilized in conventional QFD. This study proposes a way to minimize trade-offs as much as possible. We internalize trade-offs amongst decision criteria based on five BN states. The BN helps to narrow down to the best-case scenario. AgenaRisk software was used to compute the BN with ranked nodes. The procedure is as in Section 3.2.3.

4.6 | Determine the Causal Nexus of the Decision Criteria

The correlation matrix was used to determine the causal nexus of the decision criteria. The BN was determined and constructed using AgenaRisk software, as shown in *Fig. 7*. A unidirectional arrow was used to link criteria that are directly connected.

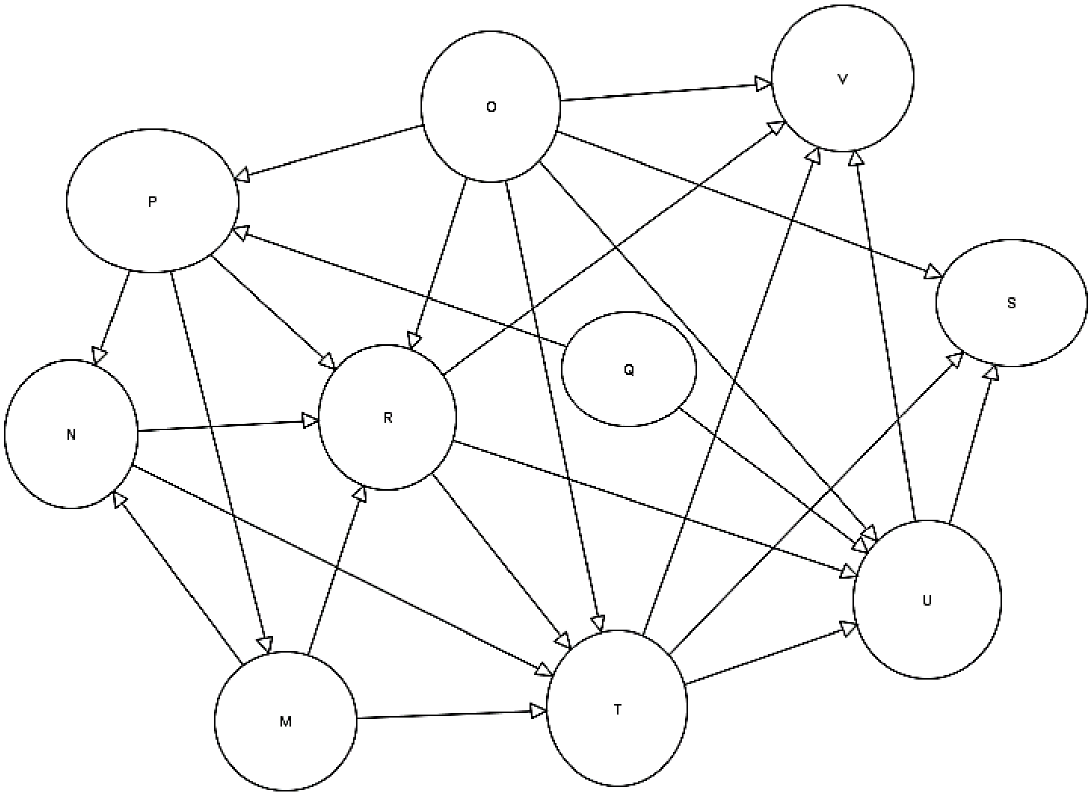


Fig. 7. Causal nexus based on correlation matrix.

4.7 | Assign States of Bayesian Networks

We use ranked nodes to assign the states of Bayesian networks.

Node states for each criterion are classified into five categories, as shown below.

4.8 | Apply Ranked Nodes in the BN

We use TNormal distribution, WeightedMean as the ranked node function, and a variance of 0.005, as shown in *Fig. 8*. AgenaRisk software automatically computes the BN model [28]. An example is given in *Fig. 9*.

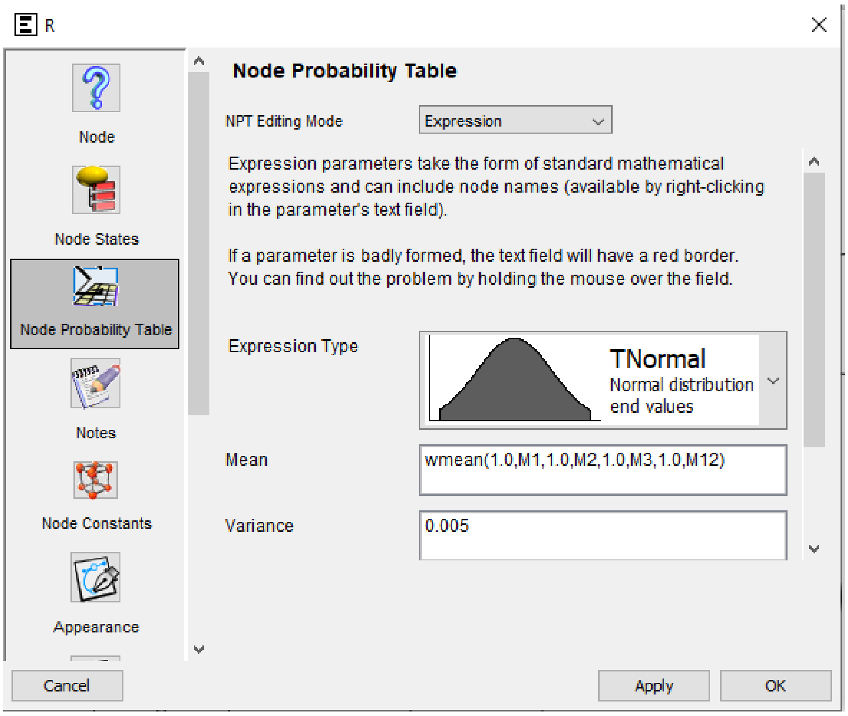


Fig. 8. Ranked nodes expressions.

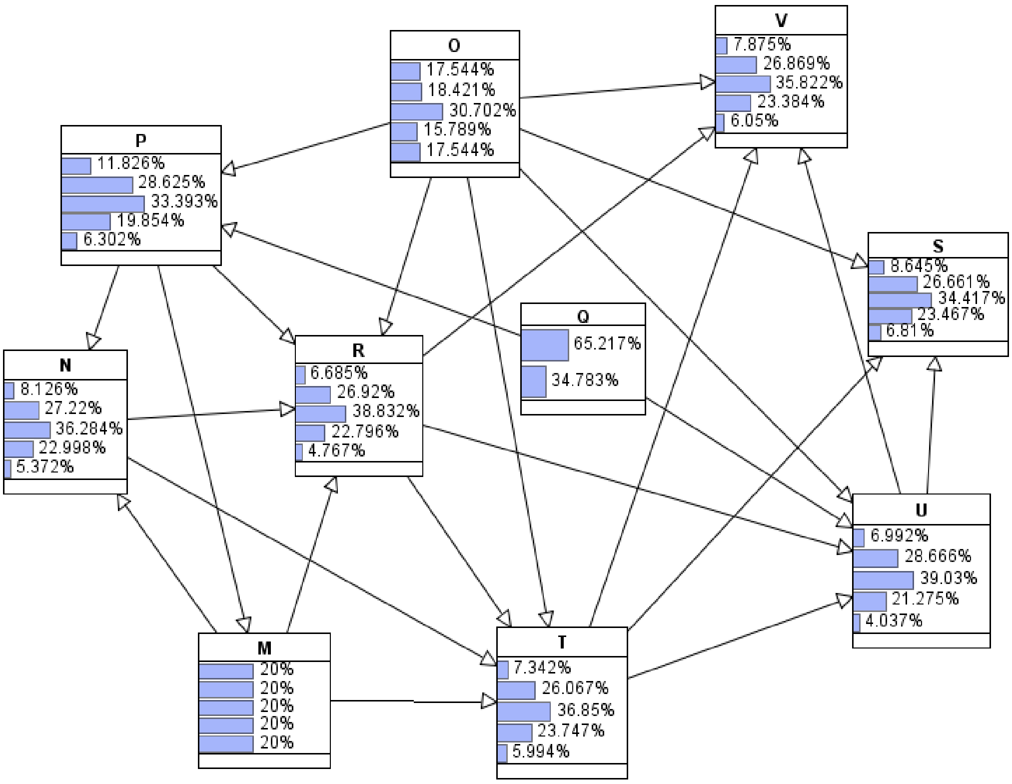


Fig. 9. Initial BN model automatically computed by agenarisk software.

4.9 | Qualitative Performance of Alternatives

Participants rated their familiarity with the performance of cross-border 3PL providers concerning each decision criterion on a five-point ordinal scale shown in *Tabel 3*. Their judgment is presented in *Tabel 4*.

Table 3. Node states of criteria.

Criteria	M, N, O	P, R, S, T, U, V	Q
Node states	Very slow	Very low	Provided
	Slow	Low	Not provided
	Medium	Medium	
	Fast	High	
	Very fast	Very high	

Table 4. Qualitative performance of alternatives with respect to criteria.

	M	N	O	P	Q	R	S	T	U	V
DHL	Very fast	Very Fast	Very fast	Very high	Provided	High	Very high	Very high	High	Very good
TNT	Slow	Medium	Medium	Medium	Provided	Low	Medium	Medium	Low	Medium
EMS	Medium	Fast	Fast	High	Provided	Medium	High	High	Medium	High
FedEx	Fast	Very Fast	Very fast	Very High	Not provided	High	Very high	Very high	High	Very good
UPS	Fast	Fast	Very fast	Very high	Provided	High	High	Very high	High	Very good
Aramex	Very slow	Medium	Medium	Low	Provided	Very low	Medium	Medium	Very low	Medium

4.10 | Quantitative Performance Probabilities of Alternatives

The network is given evidence through language phrases demonstrating knowledge of the project team on 9 out of 10 criteria. By considering the causal nexus between criteria, BN converts this information into probabilistic estimates and elicits the quantitative performance of the remaining criterion. For example, in *Fig. 10*, BN automatically elicits the performance of criterion O concerning FedEx as 0.867, as shown in *Fig. 11*. We conduct identical functions on all criteria for all the 3PL providers.

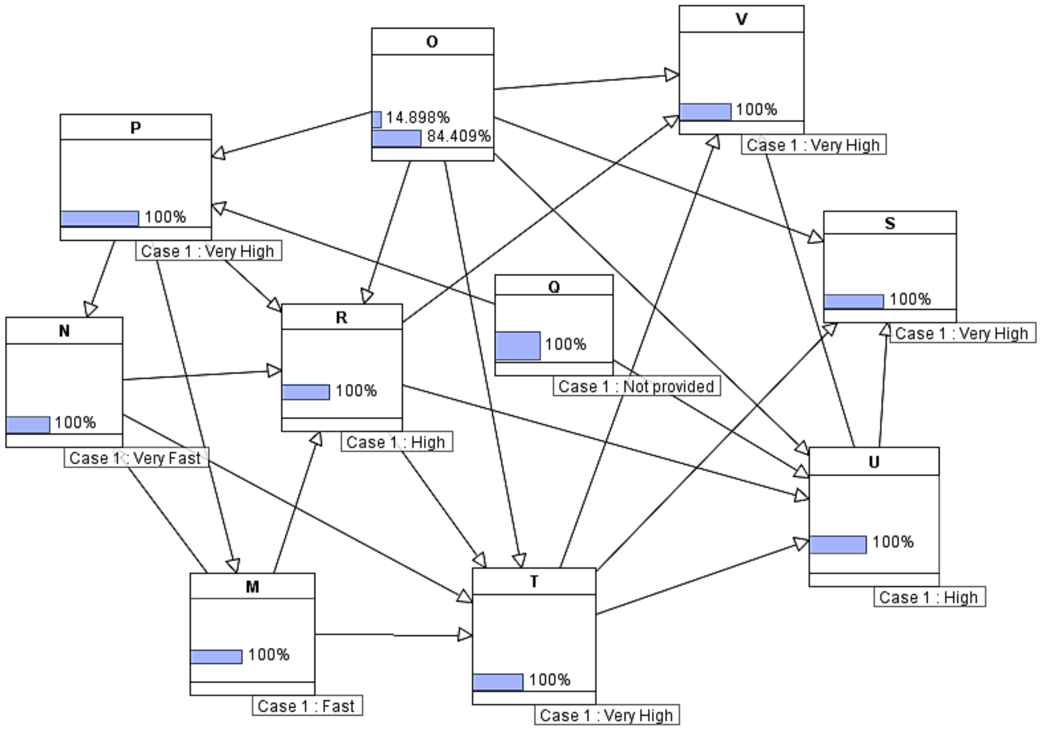


Fig. 10. Linguistic evidence as assigned to nodes with exception to criterion O.

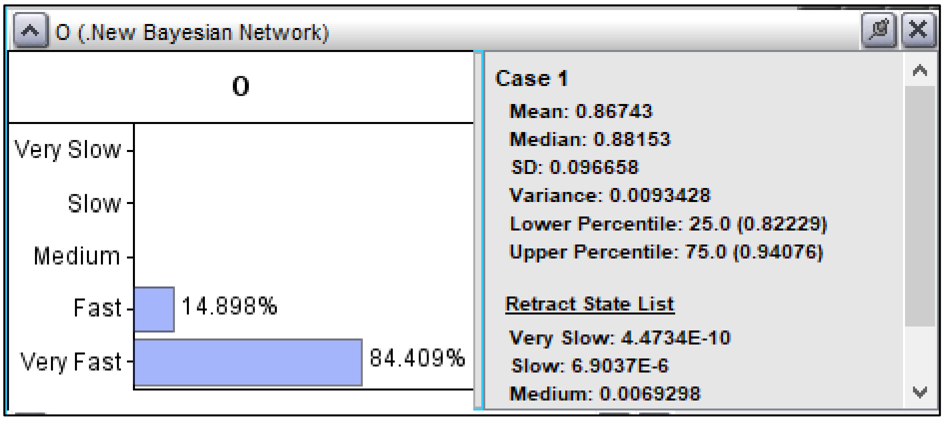


Fig. 11. Probability of criterion O with respect to FedEx.

Table 5 provides all the quantitative performance probabilities as estimated by BN. These probabilities are used as an input matrix for TOPSIS for ranking alternatives.

Table 5. Probabilities of criteria based on BN.

	M	N	O	P	Q	R	S	T	U	V
DHL	0.766	0.859	0.896	0.632	0.682	0.886	0.83	0.884	0.734	0.798
TNT	0.386	0.4	0.559	0.429	0.299	0.459	0.435	0.448	0.419	0.4
EMS	0.582	0.6	0.823	0.569	0.443	0.668	0.635	0.656	0.573	0.6
FedEx	0.768	0.8	0.867	0.85	0.682	0.854	0.83	0.843	0.842	0.798
UPS	0.616	0.8	0.896	0.605	0.682	0.845	0.83	0.759	0.676	0.798
Aramex	0.408	0.236	0.505	0.44	0.25	0.338	0.365	0.368	0.386	0.3

4.11 | Rank Alternatives

Probabilities of criteria in table xxx are used as the input matrix, while relative importance weights from HOQ are used as weights of criteria in TPSIS. In this study, TOPSIS is implemented using Python in the Jupyter Notebook, as shown in *Fig. 4*.

With a score of 0.946807, DHL is the most effective logistics mode for shipping packages from Guangzhou, China, to Cape Town, South Africa. FedEx and UPS follow it. EMS ranks fourth in order of preference. TNT and Aramex are ranked fifth and sixth, respectively, making them the least preferred. The ranking is shown in *Tabel 6*.

Table 6. Ranking of alternatives.

3PL Provider	Score	Rank
FedEx	0.845904	2
TNT	0.161362	5
EMS	0.553542	4
DHL	0.946807	1
UPS	0.780542	3
Aramex	0.013191	6

5 | Discussion

The methodology and findings of this case study indicate that low-cost logistics services are not a sufficient condition for the success of the E-commerce industry. Other factors must also be considered to serve consumers appropriately. Cross-border E-commerce traders should consider each logistics provider in its holistic nature to pay attention to all logistics activities across the supply chain.

The management must have sufficient knowledge to identify and outline the benefits of selecting a 3PL provider over the others. The service standards of the 3PL provider must fulfill both current and future needs. Involving customers in decision-making ensures that their expectations are met.

6 | Conclusion

In summary, a hybrid method was developed in this study to incorporate customer needs in the selection process. The data collected from a thorough survey and the decision criteria defined by the project team were used to construct the HOQ. Bayesian networks with ranked nodes displayed a causal nexus graph and elicited the decision matrix. It has been proven that the voice of the customer is instrumental in this regard. This study proposes a new approach for selecting cross-border E-commerce 3PL providers, combining QFD BN with ranked nodes and TOPSIS with Python stack in Jupyter Notebook. Drawing any judgments largely depends on the correlation analysis of decision criteria and the voice of the customer. Correlation analysis is not part of decision-making in the conventional QFD method. However, the proposed methodology provides a way to achieve this goal. After discussing this with the shipping experts, we analyzed the estimated effectiveness of the hybrid method, and the findings were deemed trustworthy. The new approach can be applied in many areas where businesses wish to have the voice of the customer as the genesis of selecting the best alternatives to meet client needs.

7 | Future Scope

Future works may gather additional data about customer needs in a broader region and their corresponding technical requirements, leading to a more accurate performance rating. It will involve cross-border logistics experts drawn from multiple shipping firms to participate. A more extensive data collection would provide more insightful and resilient results.

Incorporating neural networks into QFD extended with MCDM is another fascinating path we will study. More detailed analysis and graphical description of significant customer needs and expanded decision criteria can be achieved through neural networks.

Author Contribution

N. O. L, Metodology data gathering, and computing, W. H, conceptualization, writing, and editing by N. O. L.

Founding

The authors declare that no external funding or support was received for the research.

Data Availability

The manuscript contains the data on which our study findings are founded.

Conflicts of Interest

The authors state that they have no conflict of interest.

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