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Evaluating the Barriers to Logistics Outsourcing through a Fuzzy Multi-Criteria Decision-Making Model

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ABSTRACT

Logistics outsourcing has become a common strategic practice for enterprises seeking cost efficiency and greater operational flexibility. Achieving these benefits, however, depends on the effective management of outsourcing relationships through suitable governance mechanisms. In practice, several barriers limit the realization of these advantages. With a specific focus on Africa, this study applies a fuzzy criteria importance assessment (F-CIMAS) method to systematically assess the barriers to logistics outsourcing. Data were collected from four domain experts who evaluated twenty-two identified barriers, and the proposed method was then applied to determine the relative importance of each criterion. The results reveal that congested roads and weak infrastructure, poor governance, corruption and unethical conduct, inadequate regulations, and excessive cost of business operations constitute the five most critical impediments to logistics outsourcing. The robustness of the results was further validated through a comparative analysis with F-TOPSIS, F-ARAS, F-SIWEC, and F-PIPRECIA. The results demonstrated a high degree of rank correlation and structural stability across the different methods. The study makes a meaningful contribution to the decision sciences and management literature by offering practical insights for logistics outsourcing practitioners, and it concludes by outlining clear avenues for future research.

1. Introduction

Outsourcing is regarded as a system in where an enterprise or company assigns portion of its current internal operation to another organization with the goal to enhance overall performance [1]. This phenomenon has been largely implemented in the management of the third party-logistics (3PL), where enterprises progressively depend on external logistics suppliers to assist their operations [2]. The collaborations within the 3PL suppliers generally take a strategic partnerships form and tend to

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be more complicated than the traditional relationships between the buyer and supplier. Such connections have changed into an organized approach that permits enterprises to respond more effectively to promptly varying market environments, concentrate on their main abilities and follow sustainable long-term growth strategies [3]. In outsourcing decision-making, the minimization of cost is rarely the main objective of outsourcing. Instead, enterprises highlight significant parameters like high organizational flexibility, service quality improvement, ameliorated information security, and operational performance enhancement. By involving 3PL suppliers, enterprises can put much attention to their main activities, while logistics service providers fully control the operations of supply chain, diminish operational time and costs, and eventually improve customer satisfaction [4].

The choice of an outsourcing partner is affected by various parameters comprising of information technology ability, organizational growth, competitive benefit, and operational efficiency. To stay competitive, 3PL suppliers must progressively improve the quality related to service and innovation [5], while continuing successful operations. Antecedent research shows that competitive pressures and coordination issues between supply chain players can be handled without considerably disturbing overall performance [6]. Various analytical techniques have been implemented to the 3PL choice such as optimization-based models including pricing strategies and demand ambiguity [7], and interpretive structural framing in the pharmaceutical field [8]. Latest study has also emphasized the increased significance of technology-driven logistics environments [9], while frameworks like the 5C model highlight main dimensions of durable service excellence.

A study by Alioni *et al.,* [10] emphasizes how the sub-saharan Africa (SSA) logistics environment is characterized by considerable disruption risks emerging from frequent security threats, recurrent road accidents, and acute traffic congestion. These barriers are reflected in the SSA's low performance and risk parameters. Deficient transport infrastructure, systemic corruption, and expensive trade compliance processes further increase the likelihoods of delays and logistics costs. The region's greater reliance on congested ports and road transport increase supply chain exposure to disruption. Same constraints influencing the 3PL implementation in the oil and gas manufacturing sectors [11]. Despite these barriers, Etokudoh *et al.,* [12] indicated that logistics outsourcing has diminished labor and operational related costs and enhanced performance results with most of enterprises reporting important benefits from involving 3PL suppliers [13]. Nonetheless, persistent barriers comprising deficient document handling, poor coordination following variations in management, and threats related to information leakage continue to reduce the contractual effectiveness and service quality in the region' 3PL sector [13]. Okeke [14] conducted a qualitative content analysis to identify the barriers related to logistics outsourcing in Africa (Nigeria). However, the study did not prioritize them in order of critical importance under uncertain environment, nor did it adopt a multi-criteria approach [15, 16]. The multi-criteria decision making (MCDM) approaches have been seen to be a prominent approach which can overcome the uncertainties in real-life situations [17- 19]. Our study tries to fill these gaps by using fuzzy criteria importance assessment (F-CIMAS) method to comprehensively assess and rank these barriers related to the logistics outsourcing in an uncertain environment.

The remaining of the paper consists of six sections: Section 2 Literature review, Section 3 Problem definition Section 4 Methodology, Section 5 Application, Section 6 Comparative analysis, Section 7 Findings and discussions, Section 8 Managerial implications, and Section 9 Conclusion and future recommendations.

2. Literature Review

Two sub-sections are shown as bellows.

2.1 Studies Related to Logistics Outsourcing

Pani *et al.,* [20] overcome the gap of antecedent research by considering the freight trip generation as an integrated package decision and introducing a framework that permits error correlations apprehending the underlying interrelationships. Xu *et al.,* [21] adopted an enhanced gravitational search algorithm to solve the issues related to self-operation and outsourcing collaboration in integrated logistics. Görçün *et al.,* [22] introduced a new integrated approach for effective choice of road freight transportation. Zhu et al., [23] explored the influence of outsourcing management procedure (OMP) and found how it influences the two distinct categories of logistic outsourcing, separately. Ali *et al.,* [24] reveal which determinants are crucial in logistics outsourcing decisions in pharmaceutical manufacturing sector. Dong et al., [25] studied the strategy related to logistic outsourcing of a manufacturer with respect to blockchain, greenwashing, and green logistics. Giri and Sarker [26] conducted a study related to the performance improvement through the coordination of supply chain with 3PL outsourcing under production disturbance. Huang et al., [27] investigated the issue related to outsourcing risk management under the main agency framework. Table 1 indicated the studies related to logistics outsourcing.

Table 1
Logistics outsourcing related studies

Authors	Objective	Methodology
Pani *et al.,* [20]	Establishing a multi-vehicle freight trip production model	Joint package decision model
Xu *et al.,* [21]	Determine the problem related to self-operation and outsourcing cooperation	Multi-stage resource leveling model
Görçün *et al.,* [22]	Road freight transportation firm selection in 3PLs	T-SF-CRITIC-CoCoSo
Zhu et al., [23]	Determine how outsourcing management procedure enhances a successful logistic outsourcing	Survey data collected
Ali *et al.,* [24]	Examining the enablers of logistics outsourcing	Web-based questionnaire
Dong *et al.,* [25]	Influence of greenwashing and blockchain technology on logistics outsourcing	Model-based analysis
Giri and Sarker [26]	Enhancing performance by coordinating supply chain with 3PL outsourcing	Buyback and revenue sharing contract model
Huang *et al.,* [27]	Investigating outsourcing risk management issue	Contract based on delivery quality model

Note: CoCoSo- Combined Compromise Solution; CRITIC- CRiteria Importance Through Intercriteria Correlation; SF-Spherical Fuzzy.

2.2 MCDM Applications on Logistics Outsourcing

The MCDM approaches have been used in the studies related to logistics outsourcing [28]. For instance, Sarkar *et al.,* [29] adopted a new frank aggregators-driven group decision framework to assess the financial reliability of 3PL suppliers. Their findings indicated the three appropriate 3PL suppliers. Sarwar *et al.,* [30] introduced an interval rough approach for 3PL management. Nila and Roy [31] adopted an integrated subjective-objective approach for the 3PL supplier choice under sustainability dimensions. Wang and Dang [32] established a novel integrated framework according to industry 4.0 for choosing the appropriate 3PL supplier. Yang *et al.,* [33] adopted a linguistic Pythagorean technique for reverse 3PL supplier choice of electric vehicle power battery recycling. Ulutaş *et al.,* [34] adopted a model under grey environment to assess the service of 3PL suppliers for car manufacturing enterprises. Liu *et al.,* [35] proposed a group decision model for the choice of 3PRLs on self-service mobile recycling equipment. Pamucar *et al.,* [36] proposed a new integrated approach under rough environment to evaluate the 3PL supplier. Table 2 indicates the studies the MCDM applications on logistics outsourcing.

Table 2
MCDM applications on logistics outsourcing

Authors	Objective	Methodology
Sarkar *et al.,* [29]	Financial credibility assessment of 3PL supplier	DHLq-ROF
Sarwar *et al.,* [30]	Assessing the management related to the 3PL service	DIRI clouds based BWM-WASPAS and BWM-MABAC
Nila and Roy [31]	Choice of 3PL supplier under sustainable dimensions	Fuzzy LOPCOW, FUCOM, DOBI
Wang and Dang [32]	Choice of 3PL supply in the industry 4.0	Fuzzy AHP, Fuzzy MARCOS
Yang *et al.,* [33]	Choice of reverse 3PL supply of EV power	LPHF- MULTIMOORA
Ulutaş *et al.,* [34]	Assessing the service related to 3PL supplier for car manufacturing enterprise	LOPCOW, PSI, MACONT
Liu *et al.,* [35]	Choice of 3PRLs on self-service mobile recycling machine	IPHF, BWM, SOM
Pamucar *et al.,* [36]	3PL supplier evaluation	IR- BWM-WASPAS-MABAC

Note: AHP- Analytical Hierarchy Process; BWM-Best Worst Method; DHLq-ROF- dual hesitant linguistic q-rung Orthopair fuzzy; DIRI-Dual Interval Rough Integrating; DOBI- DOmbi Bonferroni; FUCOM- Full Consistency Method; IPHF-Interval Pythagorean Hesitant Fuzzy; IR-Interval Rough; LOPCOW- LOgarithmic Percentage Change-driven Objective Weighting; LPHF- Linguistic Pythagorean Hesitant Fuzzy; MABAC- Multi-Attributive Border Approximation area Comparison; MACONT- Mixed Aggregation by Comprehensive Normalization Technique; MARCOS- Measurement Alternatives and Ranking according to Compromise Solution; MULTIMOORA-Multi-objective optimization by ratio analysis with full multiplicative form; PSI- Preference Selection Index; SOM- Self-Organization Map; WASPAS- Weighted Aggregated Sum Product Assessment.

3. Problem Definition

Table 3 outlines the barriers related to logistics outsourcing in the SSA region based on the experts' opinions and precious studies [10-14].

Table 3
Barriers related to logistics outsourcing

Criteria definition	References
High cost of business operations (C1)	Expert opinion
Congested roads and weak infrastructure (C2)	[10]
Corruption and unethical conduct (C3)	Expert opinion
Inadequate regulations (C4)	Expert opinion
Supply chain disruptions (C5)	Expert opinion
Uncertain business environment (C6)	Expert opinion
Lack of advanced technology (C7)	[10]
Underdeveloped 3PL business market (C8)	
Poor governance (C9)	Expert opinion
Poor data management and information leaks (C10)	[10]
Staff resistance and unskilled 3PL personnel (C11)	[13]
Power infrastructure (C12)	[13]
Poor vendor or 3PL capability (C13)	Expert opinion
Low staff pay and poor working conditions in 3PLs (C14)	[10]
High accident rates and safety risks (C15)	Expert opinion
Loss of flexibility (C16)	[10]
Joint venture partnership intervention (C17)	[13]
Security threats and pilferage (18)	[12]
Loss of control (C19)	[13]
Change in management (C20)	[12]
Differences in organizational cultures/poor collaboration (C21)	Expert opinion
Strained relationships (C22)	[13]

4. Methodology

The determination of precise values can be achieved using either empirical data or expert judgment; however, real-world decision-making is often characterized by uncertainty, as it relies on incomplete, imprecise, and qualitative inputs from experts. Under such conditions, deterministic methods become inadequate, thereby necessitating more flexible and adaptive approaches. To address this challenge, a fuzzy set (FS) framework is employed, enabling the use of linguistic variables to effectively capture the inherent ambiguity of subjective evaluations.

In this study, a CIMAS approach, recently introduced in [37], is implemented within a fuzzy environment. This approach integrates the experience-based weighting mechanism of the original CIMAS method with fuzzy logic to obtain more reliable and robust criteria weights. It provides a novel perspective by systematically evaluating the importance of decision criteria through expert judgment. A key feature of this method is its recognition of expert knowledge and experience, assigning greater influence based on the number of years experts have devoted to the relevant field.

Since its introduction, it has been adopted in human resource management [38], nanotechnologies application in agriculture [39], manufacturing firms' capacity assessment [40], healthcare referral system [41], financial performance analysis [42], and risk assessment [43]. Fig. 1 presents the proposed methodology.

Fig. 1. Proposed methodology

The steps of the proposed method are detailed below.

Step 1. Definition of criteria set. The set of assessed criteria $C_1, C_2, C_3, \dots \dots . C_n$ and the panel of experts $E_1, E_2, E_3, \dots \dots . ., E_q$ who will be involved in this study are identified.

Step 2. Establishment of the expert panel. The significant importance or weight of every expert is calculated according to their years of experience. The Eq. (1) is used for the weight of expert calculation, guaranteeing that the sum of all experts' weights equals one.

$$W^{E_i} = \frac{E_i}{\sum_{i=1}^{q} E_i}, i = 1,2, \dots \dots \dots, q \quad (1)$$

Step 3. Initial assessment matrix establishment. The significance related to each criterion is assessed by the experts through the use of a predefined linguistic scale shown in Table 4. There is a compilation of their ratings into an initial decision matrix in Table 5, where $\tilde{x}_{ij}$ is the score attributed by expert E_i to criterion C_j.

Table 4
Scale related fuzzy linguistic assessment

Linguistic terms	Membership function
Ver Low (VL)	(1,1,2)
Low (L)	(2,3,4)
Medium (M)	(4,5,6)
High (H)	(6,7,8)
Very High (VH)	(8,9,10)

Table 5
Initial decision matrix

Experts/ Criteria	C1	C2	…	Cj	…	Cp	Expert's weights
E_1	$\tilde{x}_{11}$	$\tilde{x}_{12}$	…	$\tilde{x}_{1j}$	…	$\tilde{x}_{1p}$	W^{E_1}
E_2	$\tilde{x}_{21}$	$\tilde{x}_{22}$	…	$\tilde{x}_{2j}$	…	$\tilde{x}_{2p}$	W^{E_2}
E_i	…	…	…	$\tilde{x}_{ij}$	…	…	…
E_q	$\tilde{x}_{q1}$	$\tilde{x}_{q2}$	…	$\tilde{x}_{qj}$	…	$\tilde{x}_{qp}$	W^{E_q}

Step 4. Expert-weighted matrix calculation. Based on diverse reliability of experts, each fuzzy evaluation is weighted by the expert's specific weight W_i^E obtained from Step 2. The Eq. (2) is used for the weighted fuzzy value $\tilde{v}_{ij}$ calculation.

$$\tilde{v}_{ij} = \tilde{x}_{ij} \otimes W_i^E = \left(l_{ij}.W_i^E, m_{ij}.W_i^E, u_{ij}.W_i^E\right) \quad (2)$$

Step 5. Aggregation of Fuzzy Criteria Importance. There is an obtention of the total fuzzy significance score $\tilde{S}_j$ for each criterion C_j through the aggregation of the weighted assessments from all experts using fuzzy addition in Eq. (3).

$$\tilde{S}_j = \sum_{i=1}^{k} \tilde{v}_{ij} = \left(\sum_{i=1}^{k} l_{ij} W_i^E, \sum_{i=1}^{k} m_{ij} W_i^E, \sum_{i=1}^{k} u_{ij} W_i^E\right) \quad (3)$$

Step 6. Defuzzification. There is a conversion of aggregated fuzzy scores $\tilde{S}_j = \left(L_j, M_j, U_j\right)$ into crisp values K_j for ranking the criteria and found usage weights. A center of area (CoA) approach is adopted in this study and shown in Eq. (4).

$$K_j = \frac{L_j + M_j + U_j}{3} \quad (4)$$

Step 7. Final criteria weights computation. There is finally a normalization of the crisp values to guarantee the sum of all weights equals to 1. The Eq. (5) is used for the calculation of weight w_j for criterion j.

$$w_j = \frac{K_j}{\sum_{j=1}^{n} K_j} \quad (5)$$

5. Application

This section demonstrates the practical applicability and robustness of the proposed F-CIMAS method through a real-world case study focused on the Third-Party Logistics (3PL) industry in Africa. Despite the projected exponential growth of the global 3PL market, the African context is characterized by unique structural and operational bottlenecks ranging from infrastructural deficits to regulatory uncertainties that impede seamless logistics performance. Our adopted methodology systematically analyzes and prioritizes the critical barriers hindering the effectiveness of 3PL providers in this region, providing stakeholders with a data-driven basis for strategic intervention.

To ensure the validity and reliability of the findings, a panel of four experts was convened, possessing extensive professional experience in logistics and supply chain management ranging from 8 to 15 years. The study identifies twenty-two distinct barriers. The experts utilized a defined linguistic rating scale shown in Table 4 to assess the severity of each barrier, thereby transforming qualitative professional judgments into quantitative fuzzy data.

To provide a comprehensive assessment of the barriers hindering the operational efficacy of 3PL in Africa, this study identifies twenty-two key barriers based on a review of the logistics landscape. These barriers encompass a wide range of structural, operational, and socio-economic factors as defined in Table 3. The analysis began with the determination of expert weights, followed by the aggregation of fuzzy assessments and the final derivation of crisp criteria weights.

Step 1. The influence of each expert was weighed according to their professional experience. The total years of experience for the panel was calculated as 44 years. Table 6 presents the calculated weight (W_i^E) for each expert.

Table 6
Expert Profiles and Weights

Expert	Experience (Years)	Yi/T	Weight
E1	15	15/44	0.341
E2	10	10/44	0.227
E3	8	8/44	0.182
E4	11	11/44	0.250

Step 2. The experts assessed the 22 criteria using the linguistic scale defined in the methodology as shown in Table 7. These assessments were converted to Triangular Fuzzy Numbers (TFNs), weighed by the respective expert weights, and aggregated to form the fuzzy importance score ($\tilde{S}_j$) for each criterion. Finally, the CoA method was used to defuzzify these scores into crisp values (K_j), which were normalized to obtain the final global weights (w_j).

Table 7
Initial decision matrix

Ei/Ci	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
E1	M	H	VH	H	M	H	L	L	VH	L	L
E2	VH	VH	H	H	M	M	L	L	H	L	L
E3	M	VH	H	M	M	M	L	L	M	L	L
E4	M	H	H	H	M	M	M	L	VH	L	L
Ei/Ci	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22
E1	M	M	L	M	VL	VL	M	M	VL	L	L
E2	M	L	L	M	L	L	H	VL	VL	VL	VL
E3	M	M	L	M	VL	VL	M	VL	VL	L	L
E4	L	L	L	M	L	VL	M	VL	VL	L	VL

Table 8 presents the aggregated fuzzy importance scores ($\tilde{S}_j$) for each of the twenty-two identified barriers. These values are expressed as TFNs, characterized by a lower bound (l), modal value (m), and upper bound (u). This fuzzy representation is crucial as it effectively captures the collective judgment of the expert panel while preserving the inherent subjectivity and vagueness associated with linguistic assessments. By maintaining the data in this format prior to defuzzification, the analysis reflects the range of expert opinion and the intensity of the barriers. For instance, high-magnitude fuzzy sets such as those observed for *congested roads and weak infrastructure (C2)* and *poor governance (C9)* indicate a strong consensus regarding their severity, whereas criteria with lower intervals reflect areas deemed less critical by the decision-makers.

Table 8
Aggregated Fuzzy Criteria Weights

Criteria	Aggregate Fuzzy Number $\tilde{S}_j$ (l, m, u)
C1	(4.91, 5.91, 6.91)
C2	(6.82, 7.82, 8.82)
C3	(6.68, 7.68, 8.68)
C4	(5.64, 6.64, 7.64)
C5	(4.00, 5.00, 6.00)
C6	(4.68, 5.68, 6.68)
C7	(2.50, 3.50, 4.50)
C8	(2.00, 3.00, 4.00)
C9	(6.82, 7.82, 8.82)
C10	(2.00, 3.00, 4.00)
C11	(2.00, 3.00, 4.00)
C12	(3.50, 4.50, 5.50)
C13	(2.89, 3.89, 4.89)
C14	(2.00, 3.00, 4.00)
C15	(4.00, 5.00, 6.00)
C16	(1.48, 1.95, 2.95)
C17	(1.00, 1.45, 2.45)
C18	(4.45, 5.45, 6.45)
C19	(1.36, 2.36, 3.36)
C20	(1.00, 1.00, 2.00)
C21	(1.55, 2.55, 3.55)
C22	(1.05, 2.05, 3.05)

Table 9 details the final prioritization of the barriers following the defuzzification and normalization phases. The crisp scores (K_j), derived via the Center of Area method, provide a single representative value for each criterion, transforming the fuzzy data into actionable metrics for direct comparison. These scores were subsequently normalized to produce the final global weights (w_j), which determine the hierarchical ranking of the barriers from most to least critical.

Table 9
Crisp Scores, Final Weights, and Ranking

Criteria	Crisp Score (K_j)	Final Weight (w_j)	Rank
C1	5.9090	0.0607	5
C2	7.8180	0.0803	1
C3	7.6820	0.0789	3
C4	6.6360	0.0682	4
C5	5.0000	0.0514	8
C6	5.6820	0.0584	6
C7	3.5000	0.0359	12
C8	3.0000	0.0308	13
C9	7.8180	0.0803	1
C10	3.0000	0.0308	13
C11	3.0000	0.0308	13
C12	4.5000	0.0462	10
C13	3.8860	0.0399	11
C14	3.0000	0.0308	13
C15	5.0000	0.0514	8
C16	2.1290	0.0219	19
C17	1.4550	0.0150	21
C18	5.4550	0.0560	7
C19	2.3640	0.0243	18

Table 9
Continued

Criteria	Crisp Score (K_j)	Final Weight (w_j)	Rank
C20	1.0000	0.0103	22
C21	2.5450	0.0261	17
C22	2.0450	0.0210	20

The resulting hierarchy from Table 9 offers a clear stratification of issues, identifying *congested roads and weak infrastructure (C2)* and *poor governance (C9)* as the foremost impediment to 3PL efficiency, while designating *change in management (C20)* as lower-priority concerns, thereby providing stakeholders with a structured roadmap for strategic intervention.

6. Comparative Analysis

To validate the robustness of our methodology, a comparative analysis is conducted using four additional methodologies, F-TOPSIS, F-ARAS, F-SIWEC, and F-PIPRECIA. This comparative analysis compares the crisp scores (K_j) from the F-CIMAS model against the closeness coefficients (CC_i), utility degrees (K_i), aggregated rank crisp score (K_i) and cumulative importance (q_i) of the other two techniques. Table 10 presents the results related to this comparative analysis. The tabulated data shows consistency across all three computational methods, particularly regarding the most critical barriers. Congested roads and weak infrastructure (C2) and poor governance (C9) consistently occupy the premier positions regardless of the method applied, while change in management (C20) remains at the lowest rank. This alignment confirms the reliability of the F-CIMAS findings.

Table 10
Comparison of the results obtained by F-CIMAS

Criteria	F-CIMAS		F-TOPSIS		F-ARAS		F-SIWEC		F-PIPRECIA	
	Crisp Score (Kj)	Rank	Closeness Coeff. (CCi)	Rank	Utility Degree (Ki)	Rank	Aggregated Crisp Score (Kj)	Rank	Cumulative Importance (qj)	Rank
C1	5.9090	5	0.591	5	0.658	5	6.00	5	0.787	5
C2	7.8180	1	0.778	1	0.871	1	8.00	1	1.000	1
C3	7.6820	3	0.765	3	0.856	3	7.50	2	0.941	2
C4	6.6360	4	0.664	4	0.74	4	6.50	4	0.837	4
C5	5.0000	8	0.501	8	0.557	8	5.00	8	0.698	8
C6	5.6820	6	0.569	6	0.633	6	5.50	6	0.741	6
C7	3.5000	12	0.352	12	0.39	12	3.50	12	0.582	12
C8	3.0000	13	0.302	13	0.334	13	3.00	13	0.547	13
C9	7.8180	1	0.778	1	0.871	1	7.50	3	0.941	3
C10	3.0000	13	0.302	13	0.334	13	3.00	13	0.547	13
C11	3.0000	13	0.302	13	0.334	13	3.00	13	0.547	13
C12	4.5000	10	0.451	10	0.501	10	4.50	10	0.657	10
C13	3.8860	11	0.392	11	0.433	11	4.00	11	0.618	11
C14	3.0000	13	0.302	13	0.334	13	3.00	13	0.547	13
C15	5.0000	8	0.501	8	0.557	8	5.00	8	0.698	8
C16	2.1290	19	0.219	19	0.244	19	2.17	19	0.494	19
C17	1.4550	21	0.149	21	0.162	21	1.75	21	0.470	21
C18	5.4550	7	0.547	7	0.608	7	5.50	6	0.741	6
C19	2.3640	18	0.24	18	0.263	18	2.25	18	0.499	18
C20	1.0000	22	0.103	22	0.111	22	1.33	22	0.447	22
C21	2.5450	17	0.258	17	0.283	17	2.58	17	0.520	17
C22	2.0450	20	0.208	20	0.228	20	2.17	20	0.494	20

7. Findings and Discussion

This study provides insights into the adoption of a fuzzy MCDM Model for thoroughly analysing the barriers to logistics outsourcing in Africa. Via the F-CIMAS methodology, the following barriers are the most critical: congested roads and weak infrastructure (C2), poor governance (C9), corruption and unethical conduct (C3), inadequate regulations (C4), and excessive cost of business operations (C1).

Congested roads and weak infrastructure (C2) are the most critical barrier. This confirms with the study of Kuteyi and Winkler [44], which indicate that the increase of fuel consumption, operating costs of vehicles, and transit times along with the risk related to cargo damage and accidents is due to deficient road conditions, poor maintenance, and restricted highway capacity. They emphasized an unpredictable delivery schedule because of acute congestion in main urban corridors and at main port-hinterland connections, making it complicate for logistics service suppliers to reach contractual service-level agreements. In many countries, the lack of railway or inland waterways further concentrates the freight transportation on the already congested road networks, aggravating bottlenecks and delays. Deficient infrastructure also impedes the accessibility to rural production zones, diminishing economies of scale for outsourced logistics operations and restricting network coverage.

Poor governance (C9) is the second most critical barrier. Achola [45] confirmed this finding since their review indicated how this issue produces ambiguity and risk through the activities related to outsourced supply chain. Inadequate regulatory implementation, inconsistent policies, and corruption results in ineffective service delivery by the 3PLs providers, delays at borders and ports, and unexpected costs. The absence of transparency and unsuccessful administrative processes diminish trust, augment operational disturbance, and make difficult contract enforcement. Therefore, enterprises hesitate to outsource logistics operations and frequently prefer to maintain in-house control to diminish vulnerability to governance-related risks.

The third most critical barrier is *corruption and unethical conduct (C3)*. Okeke [14] indicated how this barrier is very critical in the African's logistics outsourcing due to the undermine trust in 3PL suppliers, unexpected delays, and increased hidden costs. According to his research, contract enforcement is weakened and the reliability in delivery is disrupted because of practices such as bribery at checkpoints, borders, and ports. Therefore, enterprises observed outsourced logistics as expensive and dangerous, disappointed them from depending on external suppliers and pushing them to maintain logistics operations in -house.

The fourth most critical barrier is *inadequate regulations (C4)*. This aligns with the study of Olubiyo [11] that indicates how this barrier impedes an effective logistics outsourcing because of weak, inconsistent, and unclear implemented regulatory frameworks. This generates uncertainty for both the 3PL suppliers and enterprises. Uncertain transport, customs, and trade regulations results in recurrent compliance issues, delays, and unpredictable costs, making it complicate to arrange and monitor outsourced logistics activities, successfully. The lack of uniformed rules related to liability, service quality, and contract enforcement reduces accountability and restricts trust between logistics suppliers and outsourcing enterprises. Therefore, outsourced logistics are viewed by businesses as vulnerable to operational disturbances and regulatory threats, disappointing larger adoption of logistics outsourcing and encouraging enterprises to maintain higher control over their supply chain operations.

Excessive cost of business operations (C1) is the fifth most critical barrier. This confirms the study of Mageto *et al.,* [46], who indicates how this barrier reduces the cost of advantages that enterprises mainly expect from involving the 3PL suppliers. Increased fuel prices, elevated vehicle maintenance expenses because of inadequate road conditions, various fees and taxes, and further informal payments considerably increase the operating costs for logistic suppliers, which are eventually passes on to clients. These elevated costs diminish the competitiveness of outsourced logistics outsourcing, restrict economies of scale, and make pricing unstable. Therefore, enterprises frequently observe logistics outsourcing as more costly and less efficient in than in-house operations, disappointing its adoption across African supply chains.

8. Managerial Implications

Based on the findings of the study, it is acknowledged that structural and institutional restrictions affected the decisions of outsourcing rather than enterprise-level incompetencies alone. Enterprises and 3PL suppliers should focus on multimodal solutions, collaborative logistics, route optimization, and practical and strategic location of warehouses to diminish vulnerability to high-risk corridors and reduce the impact of deficient infrastructure and congested roads. Due to crucial impact of inadequate regulations, corruption, and poor governance, managers must implement powerful risk management mechanisms, while involving effectively with regulatory bodies and industry associations to promote for policy harmonization and institutional reforms. Furthermore, due to high cost of business operations, there is a necessity for cost-sharing arrangements, investments in digital technologies, durable partnerships with reliable 3PL suppliers to enhance efficiency and cost predictability. Overall, managers should purchase resilient and adaptable outsourcing strategies that balance risk, control, and cost, while policymakers must handle regulatory clarity, governance quality, and infrastructure deficits to produce a favourable environment for durable logistics outsourcing in Africa.

9. Conclusions and Recommendations

In this study, an integrated fuzzy CIMAS methodology is used to evaluate the barriers related to logistics outsourcing in Africa. For that twelve barriers are identified based on experts' opinions and literature review. To collect the data, four experts are involved. The results indicated that congested roads and weak infrastructure, poor governance, corruption and unethical conduct, inadequate regulations, and excessive cost of business operations are the top 5 most critical barriers to the logistics outsourcing. While the study has made some contributions, it has some limitations. First, a small number of experts participated. Second, since Africa is comprised of 54 countries, the findings cannot be generalized because every country may have specific characteristics. Future studies should consider increasing the number of experts, conducting the study at national or regional levels. In addition, it will be important to adopt our methodology in other sectors such agriculture, healthcare, education and so on. Further new methodology can be adopted using an integration of data envelopment analysis (DEA) and fuzzy logic. In addition, we should consider the clustering approach as a future research direction given the number of African countries with various characteristics. Moreover, our method can be extended under various fuzzy extensions [47], such as Pythagorean fuzzy sets, intuitionistic fuzzy sets [48], and Neutrosophic fuzzy sets.

Author Contributions

Conceptualization, M.B.B; writing—original draft preparation, I.B. and M.B.B; writing—review and editing, I.B. and M.B.B.; visualization, C.K.K and I.B.; supervision, C.K.K.; project administration, M.B.B. All authors have read and agreed to the published version of the manuscript.

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

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