CHAPTER 4

DESCRIPTIVE ANALYSIS

Descriptive analysis identifies the various use cases of digital technologies specifically tailored for a sustainable maritime freight system. By analysing these use cases, we aimed to understand how different technologies contribute to sustainability goals in the industry. Furthermore, we modelled the contextual relationship between digital technologies and maritime freight sustainability. This involved examining how these technologies interact with various factors within the maritime industry and their collective impact on enhancing sustainability. Through this approach, we were able to provide a comprehensive framework that highlights the importance of digital technology adoption and its potential to drive significant improvements in environmental and operational efficiency in maritime freight. The decision-making methods used include:

➢ **Sub-objectives**

- Identify the key factors influencing blockchain adoption in maritime freight and quantify their impact on sustainability perspective.
- Establish the interrelationships among the key determinants influencing blockchain adoption in maritime freight.
- Determine the major constraints to the adoption of big data and AI in maritime freight industry and examine the interrelationships among such constraints & prioritize them based on their relative importance.
- Identify the constraints to the adoption of IoT in maritime freight and evaluate the impact of these constraints on its adoption.

4.1 Key determinants of Blockchain adoption and their impact on sustainability

Maritime freight transport is formulating an effort to move toward sustainability by adopting solutions from an economic, social, and environmental perspective (Bag et al., 2021; Kumar and Anbanandam, 2020). MFT is referred as a globally leading transport model providing efficient services at low cost (Hussein and Song, 2023; Bag et al., 2023a, 2023b, 2023c). Since, it is a conglomerate of multiple partners, the interchange of goods from one organization to another has to bear multiple transport documents, due to which it can hamper the movement of freight (Carlan et al., 2020; Singh et al., 2022). Thus, there is a need to implement modern technology to improve information flow and security as well as impart long-term sustainability to minimize disruptions and enhance the operational efficiency of marine freight transport. To cater issues such as effective information flow, security and long-term sustainability, alternative frameworks and solutions are currently under study (Oloruntobi et al., 2023; Gonzalez et al., 2021; Wan et al., 2022). One measure derived from the literature emphasizes the importance of embracing digitization for constructing a more sustainable and efficient maritime freight industry. Josh Bersin succinctly captures this idea by stating, "Digital transformation is not all about technology, it is about people." These words highlight the fact that the digital revolution involves more than just the adoption of new technologies; it also necessitates the development of human skills to effectively use these technologies. In essence, any valuable innovation becomes futile if organizations and individuals lack the knowledge and capacity to harness its potential (Bag and Pretorius, 2022; Otia and Bracci, 2022). Consequently, the human intellect may feel underused unless it actively engages in the process of innovation (Gurteen, 1998). Digitization comprises of various technologies in form of blockchain technology (BCT), digital twin, big data, etc. for the benefit of organizations and to hit the public in a roundabout way (Rejeb et al., 2021; Reiman et al., 2021). Among them, the most appropriate technology seems to be the adoption of BCT for effective information flow and security, with the main objective of tracking the actual position of goods over time, increasing logistics visibility and reducing risk and cost (Rogerson and Parry, 2020).

To balance the overall transportation cost resulting from documentation, BCTs can eliminate unnecessary paperwork, as well as reduce bureaucracy. Also, it calls for other intelligent and efficient solutions such as digitization, automation and streamlined processes (Kumar and Amin, 2022; Laroiya et al., 2020). However, several factors contribute to the effective implementation of BCT in maritime freight industry either positively or negatively (Balci and Surucu-Balci, 2021; Treiblmaier et al., 2021). A number of studies illustrate that to procure benefits of BCT, it is necessary to have sufficient knowledge of the organizational conditions required to overcome the technical uncertainty associated with blockchain (Chin et al., 2022). At the same time, other factors related to BCT's such as end-to-end transparency and openness raise concerns about data privacy breaches (Panghal et al., 2022; Tiron-Tudor et al., 2021). A number of studies highlight that the adoption of BCT in MFT is a research topic for the emerging technology sector and the full adoption of its benefits is still a matter of investigation (Tan and Sundarakani, 2020; Yang, 2019; Dong et al., 2020). The proposed study attempts to bridge this research gap by weighing the factors to implement BCT for MFT.

4.1.1 Factors influencing Blockchain technology adoption

Blockchain implementation, which offers a unique set of opportunities for industries, still remains somewhat incomplete due to some constraints. This is because we are not fully equipped to remove those potential barriers and build a bridge to the benefits that can come from embracing BCT. Therefore, a taxonomy of BCT adoption in MFT enables us to understand the specific issues, critical factors, and benefits of adopting it to make the promising business performance sustainable (Russo-Spena et al., 2023). There has been little development concerning the quantification of critical factors to blockchain adoption. There were only a few attempts to assess blockchain implementation, which are not specifically focused on the MFT sector. Figure 4:1 highlights the conceptual framework of the analysis containing the four constructs of blockchain adoption. Accordingly, factors to the adoption of BCT can be classified along several dimensions. Factors influencing the adoption of BCT can be classified based on several dimensions such as the specific department affected and whether the barrier originates internally or externally to the organization. A model is prepared using SEM technique for the observation of 18 factors obtained from literature review and expert opinion. The 18 factors of BCT adoption in MFT are in the form of observed variables. These are further divided into four dimensions and are represented in Table 4:1.

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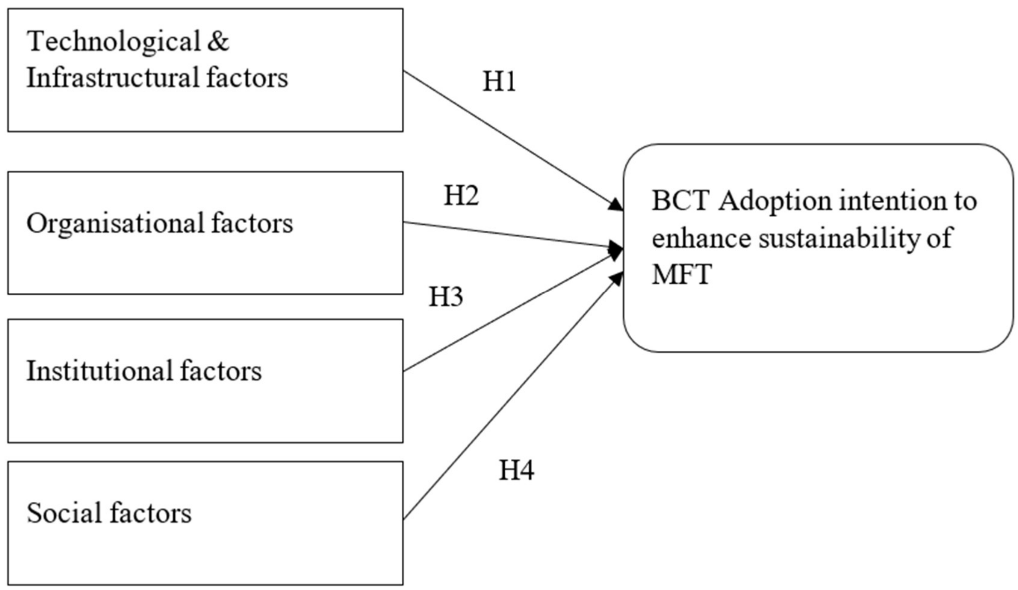

Figure 4:1 Conceptual framework of BCT Adoption

H1. The latent variables of Technological factors have a significant and positive impact over the second-order latent variable of blockchain adoption.

H2. The latent variables of Organizational factors have a significant and positive impact over the second-order latent variable of blockchain adoption.

H3. The latent variables of Institutional factors have a significant and positive impact over the second-order latent variable of blockchain adoption.

H4. The latent variables of Social factors have a significant and positive impact over the second-order latent variable of blockchain adoption.

Table 4:1 Selected factors influencing blockchain adoption in MFT

Group	Code	Factors with supported References	Final Survey
Technological & Infrastructural	TI1	Intermodal infrastructure (railways, waterways connectivity with highways) and navigational infrastructure (Shardeo et al., 2020)	√
	TI2	Perceived Benefits (Orji et al., 2020b)	√
	TI3	Development of digitalization strategy across national, urban, company, and corridor levels (Zhou et al., 2020)	√
	TI4	Development of smaller ports (Gerlitz and Meyer, 2021)	√
	TI5	Trade Imbalance (Civelek and Artar, 2019)	√
Organisational	O1	Monitoring among companies, and tracking fleet/fuel use (Irannezhad, 2020)	√
	O2	Stakeholder's mindset towards digitalization (Balci and Surucu-Balci, 2021)	√
	O3	Security and privacy best suited to the industry with a large number of small owner/operators (Farah et al., 2024; Orji et al., 2020b)	√
	O4	Stakeholder consultations before policy decisions (Zhou et al., 2020)	√
	O5	Initial investment cost (Li et al., 2021)	√
Institutional	I1	Trust over digital technology (Irannezhad, 2020)	√
	I2	Stringent enforcement of policies and regulations (Shardeo et al., 2020)	√
	I3	Competitive pressure (Orji et al., 2020b)	√
Social	S1	Coordination among stakeholders (Liu et al., 2021)	√
	S2	Interest in fuel efficiency improvements and urban freight (Farah et al., 2024)	√
	S3	Dedicated sustainably enabled digital freight training course to improve awareness and capability across a diverse set of stakeholders (Balci and Surucu-Balci, 2021)	√
	S4	Support from Senior Management (Zhou et al., 2020)	√
	S5	A platform to discuss and share insights on green freight initiatives and challenges (Zhou et al., 2020)	√

4.1.2 Methodology

SEM approach is applied in integration with artificial intelligence (AI) techniques in this study. The statistical analysis is carried out in two phases, with SEM related to the first step and the second one being appraised with an ANN model. SEM is further extended with validation of measurement model and structural model hypothesis testing. Next, ANN is applied to train and test the proposed model and quantify the influential power of the independent factors on the dependent one. The study first highlighted all relevant factors, followed by building a model using SEM to predict BCT adoption based on the severity of measured variables and latent variables. In this way, the factors are ranked based on their indices. The broad approach to this task is evident by Figure 4:2.

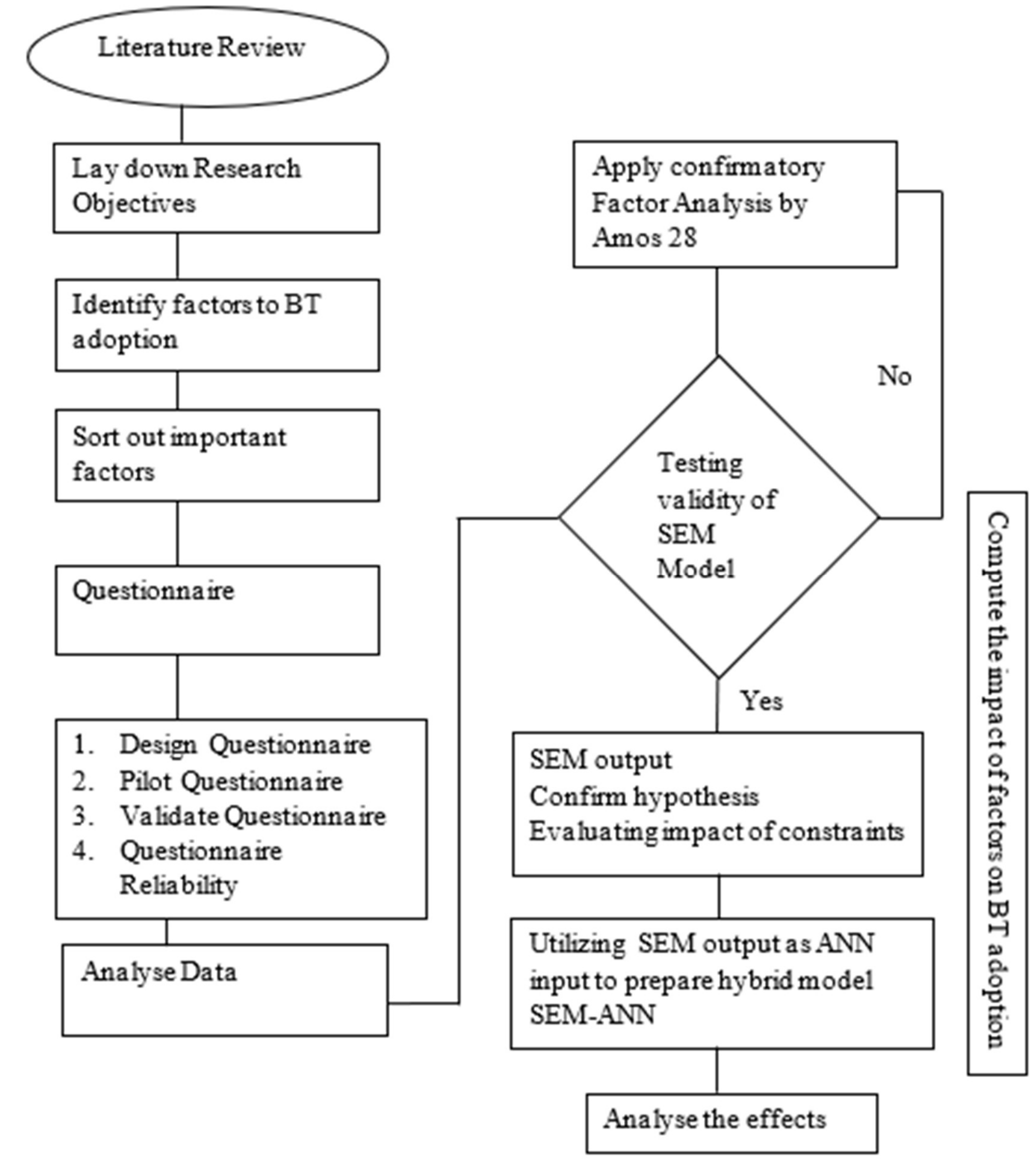

Figure 4:2 Flowchart of SEM-ANN method

4.1.2.1 Questionnaire development

A total of 18 influencing factors were shortlisted for the adoption of blockchain in MFT based on existing literature and experts' suggestions. After that, the identified factors were divided into four main dimensions, in which the first three are technological, organizational, and institutional and the last and fourth one is the social dimension. We have not taken any such factor which has not appeared at least three to four times in previous works. In this study, the factors that appeared at least three times in the literature was considered to ensure its relevance and significance. Therefore, the specific threshold for inclusion is a minimum of three instances, with some factors potentially appearing four times or more in the literature. This approach ensures that the factors selected for analysis are supported by sufficient empirical evidence and have demonstrated consistent importance across multiple studies. In this way, the primary list is formed by including a total of 18 factors distributed among four dimensions, namely, Technological, and infrastructural, Organizational and Social.

Twelve experts from the marine industry with over 10 years of experience were included in this study. Delphi technique was used to obtain consensus among experts on the adoption of BCT. The final list of factors was obtained in three phases. In the first phase, it was checked whether any factor was missed. The second phase was to eliminate unimportant factors, and the last one was concerned with the importance of factors. In this way, a total of 18 factors were obtained by disclosing the list of factors to the experts, summarizing their responses and re-circulating them. The questionnaire was segregated into two sections, the first section was about the general details of the respondents and the second was about the intensity of influence of the key factors on blockchain adoption. A five-point Likert scale was adopted for this study.

4.1.2.2 Sample size and sampling technique

Comrey and Lee (1992) recommended a sample size of over 200 respondents as an adequate sample size for applying exploratory factor analysis. In addition, Chou et al. (2000) and Afthanorhan (2013) stated the requirement of at least 200 samples for SEM analysis. On this basis, a total of 400 survey questionnaires were circulated among the functionaries related to the maritime industries. Out of which a total of 250 respondents responded, which works out to a response rate of 62%. This sample size seems reasonable for the purpose of drawing logical conclusions. The sample was collected from academia and industry experts present in India. This sample was precisely selected because highly educated person anticipates the benefits and problems of early adoption of technological innovations (Aljawder and Abdulrazzaq, 2019). An online brainstorming session was conducted with professionals to conduct a pilot test for the questionnaire and simultaneously validate the questionnaire's reliability with the maritime industry experts.

4.1.2.3 Data collection

The respondents were managers, analysts and coordinators belonging to the Department of Maritime Transportation as well as professors and research scholars from academia. These recognized individuals were contacted by sending Google Forms through email, and WhatsApp Messengers so that no valid person is left out and at the same time it is also ensured that a respondent can play their role only once. A total of 400 forms were distributed in which only 150 responses could be collected within four weeks of the timespan, which was insufficient for our purpose. As a result, we had to send a follow-up reminder, which was followed by 100 more responses. Thus, adequate answers were obtained at the rate of 62.5%. In the survey, 30 (12%) were managers, 37 (14.8%) were coordinators, 25 (10%) were analysts, the remaining 68 (27.2%) were professors and the remainder were scholars. About 35.2% of these people had more than 12 years of experience in their respective domains.

4.1.2.4 Confirmatory factor analysis (CFA)

CFA helps to reveal the structure of the observed variables and to verify their measurements. It can also be used to estimate the reliability and validity of measurements through precise specifications of the constructs and their indicators, even before the data are actually tested (Hair et al., 2017). Thus, it is useful in validating the hypothesis.

4.1.2.5 Fit indices

So far, it has been observed that there are two types of fit indices: First goodness of fit (GoF) indices and second badness of fit indices. GoF indices, whatever indices are there, their maximum values toward 1 are considered good. On the contrary, the lower the value of badness of fit indices means the closer it is to zero, the better it is. Then, certain measures are evaluated with their standard values to test the GoF. The goodness of fit index (GFI) $\geq$0.950; adjusted goodness of fit index (AGFI)$\geq$0.8; normed fit index (NFI) $\geq$0.8; comparative fit index (CFI) $\geq$0.950 very good; > 0.9 conventional; >0.8 sometimes acceptable, etc. are included in the GFIs. Furthermore, badness of fit indices such as the value of the root mean square error of approximation (RMSEA) is less than

0.050, the better it is. The closer the root mean square residual (RMR) is to zero, the better it is.

4.1.3 Data analysis and results

The researchers have long relied on statistical analysis to justify their experimental results. For this reason, here also with the help of SPSS 28, the validity of the collected data was checked along with its eligibility for adoption in SEM. The purpose of this investigation is to maintain the credibility of the data and to determine the mutual understanding among the respondents. A Cronbach's alpha coefficient greater than 0.7 is considered good (Balhara et al., 2020). The alpha coefficient for this task is also well above the minimum limit, which is 0.828. The individual alpha coefficients and validity of all factors are shown in Table 4:2. The two-tailed significance value in Table 4:2 is 0.000 which is smaller than 0.05, indicating that all the identified factors are supported. Also, the KMO measurement of 0.699, which is higher than the acceptable value of 0.60, indicates that the sample size is sufficient to conduct the survey. After that, Bartlett's test of sphericity came out to be 0.000, which was less than the appreciable value of 0.05, thus our data passed Bartlett's test of sphericity.

Table 4:2 The reliability analysis

GROUPS	No.	RELIABILITY	Sig. (2-tailed)
TI	5	0.864	0.000
ORG	5	0.828	0.000
INS	3	0.805	0.000
Social	5	0.848	0.000
Total	18	0.828	

KMO value=0.699

Bartlett's Test of Sphericity (significance of 0.00)

4.1.3.1 Model fit

SEM model must satisfy the GoF criteria. In the present study, a second-order CFA model is developed using AMOS 28. Consequently, the validity of the internal structure model results are examined by taking into account the predictive competence of the model and the relationships between constructs. The fit indices of the SEM model are listed in Table 4:3. The results suggest that the fit indices of the final SEM model are adequate based on the parameters set.

4.1.3.2 Model refinement

A theoretical model is built on the factors of blockchain engagement with the aim of making MFT sustainable. SEM is built on two pillars, the first measurement model, and the second structural model. Factor analysis gives rise to measurement models with a purpose to define exogenous variables whereas, the structural model focuses on predefined parameters for the simulated model. Two types of strategies for model refinement are well known in factor analysis; one is to remove those factors whose correlation with their latent variable is less than the standard value and the second remove those links whose relationship is too low.

Whereas AMOS software provides study methods through analysis including interrelationships of variables, variance analysis, regression analysis, and factor analysis. This produces more accurate models than those generated by traditional multivariate statistical methods. Figure 4:3 shows the investigation of the initial model with the help of AMOS software.

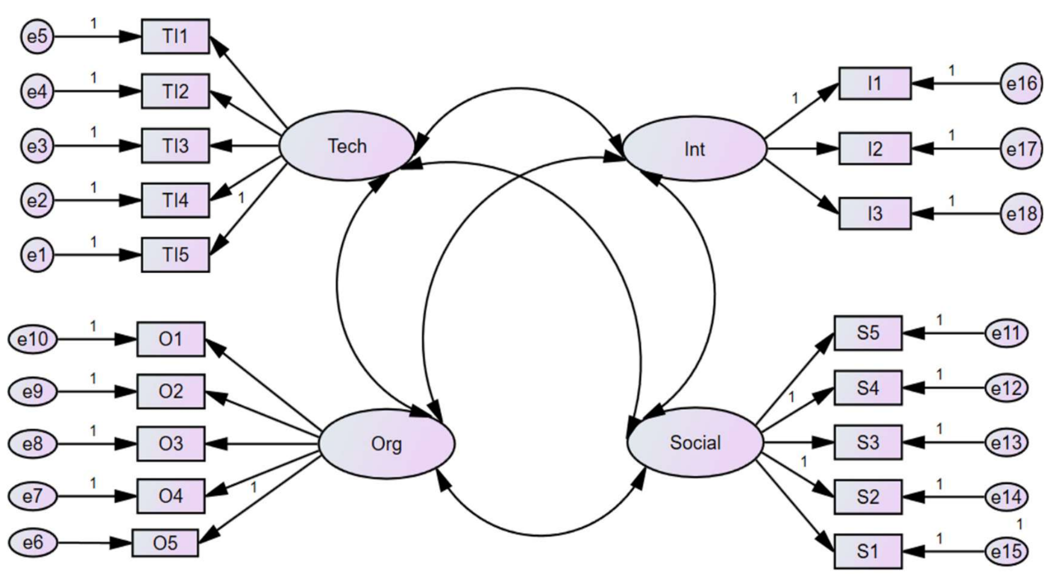

Figure 4:3 Initial SEM for factors of BCT adoption in MFT

Table 4:3 Model fit indices

GOF measures	Initial Model	Final Model
The Goodness of fit index (GFI)	0.810	0.922
Root mean square error of approximation (RMSEA)	0.054	0.037
The comparative fit index (CFI)	0.803	0.852
The Tucker-Lewis coefficient (TLI)	0.789	0.832
Root mean square residual (RMR)	0.060	0.030
Adjusted Goodness of fit (AGFI)	0.822	0.898

The reliability, internal consistency, and validity measures (which can be convergent, and discriminant) of the constructs suggested by Hair et al. (2017) are known to be good implements to assess the model. The reliability test accounts for the consistency among the latent factors that can be handled from the constructed model. As per the study by (Hair et al., 2017), if the outer factor loading of the observed variables is less than 0.5 then it is not considered appropriate. Hence, it will be discarded, and variables with loadings greater than 0.5 will be appreciated. Thus, the composite reliability is derived with the help of below equations. It is evident from Table 4:2 and Table 4:4 that all the factors have Cronbach alpha coefficient and composite reliability higher than 0.7; consequently, the estimates can be trusted. Further, Table 4:4 also derives the Average Variance Extraction (AVE) of the factors from below equation, with all AVE values greater than the standard value of 0.5.

The final structural equation model of the factors of BCT adoption in MFT is demonstrated in Figure 4:4.

$$CR = \frac{(\sum \lambda i)}{(\sum \lambda i)^2 + (\sum \varepsilon_i)} \qquad 4\text{–}1$$

$$\varepsilon_i = 1 - (\lambda i)^2 \qquad 4\text{–}2$$

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{\sum_{i=1}^{n} \lambda_i^2 + \sum_{i=1}^{n} Var(e_i)} \qquad 4\text{–}3$$

Where λi stands for the standardized factor loading for the ith item. ε represents the error variance for the ith item, and the number of items is followed by n. $Var(e_i)$ represents the variance of the error of the ith item.

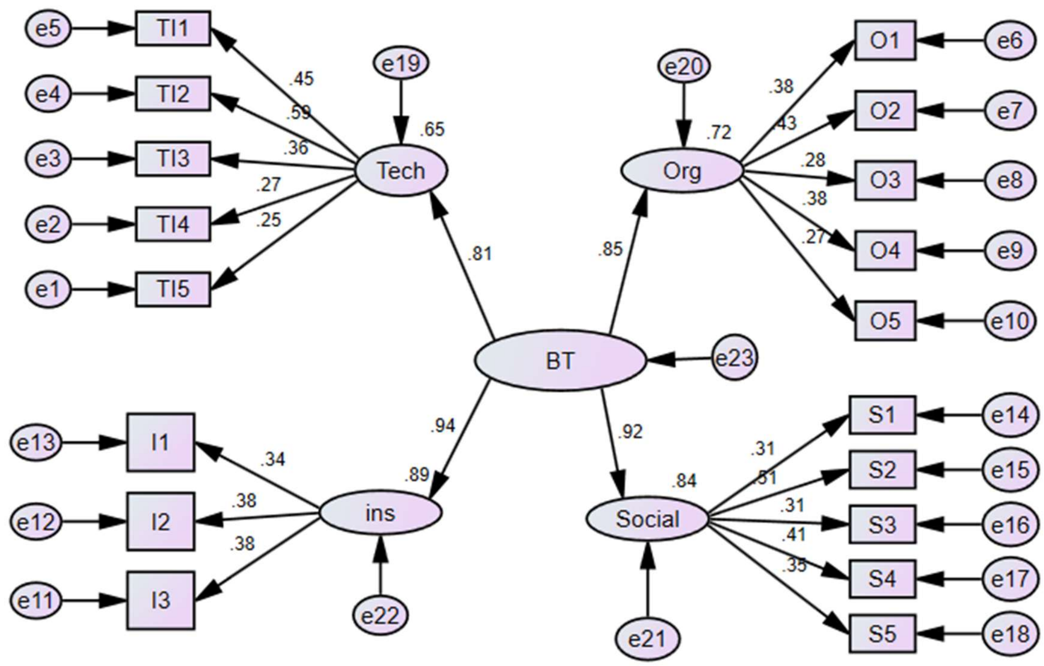

Figure 4:4 Final SEM for Factors of BCT adoption in MFT

The regression analysis obtained from the output of the final model for each latent variable is as follows. Henceforth, latent variables Tech, Org, Ins, Social, and BT-adoption are represented via. below equations respectively.

$$Tech = 0.45TI1 + 0.59T2 + 0.36T3 + 0.27T4 + 0.25T5 \qquad 4\text{–}4$$

$$Org = 0.38O1 + 0.43O2 + 0.28O3 + 0384O4 + 0.27O5 \qquad 4\text{–}5$$

$$Ins = 0.34I1 + 0.38I2 + 0.38I3 \qquad 4\text{–}6$$

$$Social = 0.31S1 + 0.52S2 + 0.31S3 + 0.41S4 + 0.35S5 \qquad 4\text{–}7$$

$$BT = 0.81TI + 0.85O + 0.94I + 0.92S \qquad 4\text{–}8$$

This confirms that the external model measurements are accurate. After that, the next step is to investigate the internal structure model results of the final SEM model. This is accomplished by checking the Goodness-of-Fit (GoF) index and Badness of Fit indices. These indices are suitable criteria for inferring the internal structure of the model. GoF indices are used to assess whether the model is representing the observed data appropriately. A good fit indices describes the characteristics of the model such that the model is liberal and appreciable.

Table 4:4 Estimates of the observed variables

Item	Factor Loadings	Composite Reliability (C.R.)	AVE value
O1 >> Org	0.833	0.87	0.575
O2 >> Org	0.672		
O3 >> Org	0.722		
O4 >> Org	0.803		
O5 >> Org	0.750		
S1 >> Social	0.762	0.875	0.584
S2 >> Social	0.823		
S3 >> Social	0.755		
S4 >> Social	0.765		
S5 >> Social	0.713		
TI1 >> Tech	0.894	0.889	0.619
TI2 >> Tech	0.705		
TI3 >> Tech	0.798		
TI4 >> Tech	0.654		
TI5 >> Tech	0.858		
I1 >> Ins	0.847	0.806	0.587
I2 >> Ins	0.582		
I3 >> Ins	0.840		

4.1.3.3 Hypotheses testing using SEM

SEM analysis built on hypothetical estimates and earlier empirical results is considered appropriate in the nascent age even if it does not follow the norms. This SEM model incorporates second-order CFA, in which BCT adoption in sustainable MFT is a second-order latent variable that is saturated on four first-order latent variables. Those four first-order latent variables include Technological (Tech), Organizational (Org), Institutional (Int), and Social. There are also exogenous and endogenous latent constructs in this model. In this way, the existing model is prepared by being influenced through 4 main dimensions. The developed hypotheses were investigated through SEM. The R-squared values given in Table 4:5 indicates that the model has high predictive power. The percentage of variance accounts for 65.1% for technological factors 72.5% for organizational factors and 84.3 for Social Factors with 89.3 Institutional Factors.

Table 4:5 R^2 of endogenous constructs

S. No.	Hypothesis	R^2	Results
1	Tech	0.651	Moderate
2	Org	0.725	High
3	Ins	0.893	High
4	Social	0.843	High

Thereafter, the SEM method is used to find out the inferences and conclusions which has given support to verify the stated hypotheses. The path model displayed in Figure 4:4 addresses the relationships between the variables considered (Hair et al., 2010; Panayides & Lun, 2009). The path coefficients are displayed in the model and are given the name beta. The hypotheses are tested based on loadings or the basis of standard values of beta. The beta (beta) and p-values associated with these are displayed in Table 4:6. The predicted values attached to the constructs attempt to demonstrate their significance to the dependent variable "blockchain adoption". BCT is treated as the dependent variable and the rest as independent variables. All four hypotheses are accepted based on the data collected through the survey, showing significant p values (< 0.050). Of course, the researchers also gave their full support to these hypotheses. Any null hypothesis is also expelled out on the basis of these p values and the positive value of beta also has a part in the acceptance of the hypothesis. The results show that the maximum value of the β coefficient is a strong support for H3. Subsequently, H4 is followed by H2. Finally, H1, whose strength of association is lower than the rest but is within the standard values, is also accepted.

Table 4:6 Estimates of the structural model

			Standardized Estimate	Unstandardized Estimate	S.E.	C.R.	P
Org	<---	BT	0.851	1.105	0.403	2.74	0.006
Ins	<---	BT	0.945	1.328	0.468	2.837	0.005
Social	<---	BT	0.918	0.995	0.420	2.36	***
Tech	<---	BT	0.807	0.642	0.285	2.253	0.024
TI5	<---	Tech	0.25	1			
TI4	<---	Tech	0.275	1.202	0.535	2.244	0.025
TI3	<---	Tech	0.359	1.516	0.607	2.498	0.012
TI2	<---	Tech	0.588	2.494	0.896	2.783	0.005
TI1	<---	Tech	0.448	1.983	0.745	2.661	0.008
O1	<---	Org	0.376	1			
O2	<---	Org	0.429	1.167	0.347	3.364	***
O3	<---	Org	0.276	0.702	0.267	2.632	0.008
O4	<---	Org	0.379	1.053	0.331	3.179	0.001
O5	<---	Org	0.273	0.737	0.282	2.613	0.009
I1	<---	Ins	0.382	1			
I2	<---	Ins	0.378	0.97	0.294	3.299	***
I3	<---	Ins	0.337	0.843	0.272	3.099	0.002
S1	<---	Social	0.312	1			
S2	<---	Social	0.512	1.789	0.537	3.33	***
S3	<---	Social	0.314	0.98	0.357	2.747	0.006
S4	<---	Social	0.411	1.343	0.433	3.104	0.002
S5	<---	Social	0.347	1.137	0.394	2.886	0.004

4.1.3.4 Artificial Neural Networks (ANN) for Prediction of Blockchain Adoption

ANN proves to be helpful in simplifying the complexities that SEM is unable to do. SEM is beneficial in simplifying complex problems in decision-making processes, but ANNs are adept at providing extreme simplification to those processes as well. Compared to traditional statistical techniques, ANNs appear to be more accurate, robust, and responsive. Non-compensatory distributional assumptions such as normality, linearity and homoscedasticity are not demanded by ANNs, unlike structural equations.

Similar to previous research studies, this study also adopts a two-stage hybrid SEM-ANN method. As evident from the previous sections, the study first employed SEM, which tested the hypotheses and resulted in significant predictive factors. Then, those factors are used as inputs for the ANN so that the relative relationship between those factors can be highlighted. To measure these relationships, a three-layer feed-forward back-propagation multi-layer perception ANN is implemented. In these three layers, one layer is composed of inputs, the second hidden, and the third output. To implement this type of ANN, SPSS version 26 is used. To overcome problems like overfitting, the 10-fold validation method is coordinated with data splitting 80:20. Here feedforward ANN refers to the signals being forwarded from the input layer to the output layer in the network. It works on supervised learning, which stores the acquired knowledge in the form of a network, then unfolds as it repeats over a pattern of input and output that has been determined.

The error is assigned with the responsibility for the difference among the desired and observed output. First, the errors are computed, and then the resulting errors are further fed to the network, which adjusts the synaptic weights to reduce these errors, as a result, increasing the accuracy of the predicted results. The number of neurons is the same as the number of inputs (i.e., factors) that make up the input layer. Similarly, the output layer is made up of a number of neurons equal to the number of outputs (which are our dependent variables).

The sigmoid function is employed to build the neural network model, which serves as the activation function for both the hidden and output layers. The root mean square error (RMSE) for training and testing of all ten neural networks is also calculated separately which is a reflection of the assessment of the predictive accuracy of the model. The RMSE values along with their mean and standard deviation values are arranged in Table 4:7. The mean value of RMSE extracted for the stability and accurate prediction performance of the neural network is 0.156 for training and 0.159 for testing, which is relatively low.

Table 4:7 RMSE values for training and testing routines

Neural Networks	Sum of square error (Training)	Sum of square error (Testing)	RMSE (Training)	RMSE (Testing)
ANN 1	4.246	1.166	0.159446	0.141815
ANN 2	3.872	1.701	0.157545	0.156991
ANN 3	3.578	1.984	0.152915	0.165992
ANN 4	3.992	1.587	0.158458	0.155078
ANN 5	3.863	1.721	0.154424	0.165259
ANN 6	3.431	2.121	0.153303	0.163862
ANN 7	3.651	1.916	0.154981	0.162026
ANN 8	3.749	1.812	0.152132	0.169583
ANN 9	3.614	1.975	0.155745	0.161188
ANN 10	3.725	1.891	0.160271	0.153739
Mean	3.772107	1.787356	0.155922	0.159553
Std. Dev.	0.232708	0.268871	0.002864	0.008007

The sensitivity analysis is executed through ANN to gauge the predictive capability of each input factor as shown in Table 4:8. The assessment of the normalized importance of these factors involves dividing their relative importance by the maximum importance and representing this value as a percentage (Das et al., 2021). Thus, results show that the most important factors for BCT adoption in MFT are Sustainably Enabled Digital Freight Training (S3), Initial Investment cost (O5), and Trust over Digital Technology (I1).

4.1.4 Discussion

The objective of this study is to identify the potential factors responsible for embracing BCT adoption in MFT. The results of the study explain with illustrations that all the factors are important at their respective places. However, factors such as social, institutional, and organisational have a more significant impact on BCT implementation in MFT. This significance is determined through the evaluation of their β coefficient values in SEM analysis, as clearly depicted in Table : 4:6 and Figure 4:4. Similarly, SEM analysis has revealed important factors influencing blockchain adoption.

The findings of our study underscore the significance of three key factors in driving the adoption of Blockchain Technology (BCT) in Maritime Freight Transportation (MFT):

Sustainably Enabled Digital Freight Training (S3), Initial Investment Cost (O5), and Trust over Digital Technology (I1). These factors play crucial roles in leveraging the transformative potential of blockchain within the maritime industry.

Sustainably Enabled Digital Freight Training (S3) stands out as a foundational element in preparing the workforce to effectively engage with blockchain technology. A workforce that has a deep understanding of how BCT operates. In addition, a technologically literate workforce that is able to effectively integrate new technologies to address current challenges. By providing specialized training programs tailored to the unique needs of the maritime sector, organizations can equip their personnel with the necessary skills and knowledge to harness the benefits of blockchain. This not only enhances technical proficiency but also fosters a culture of innovation and adaptability within maritime organizations, driving sustainable growth and competitiveness. A study by Orji et al., (2020a) has also supported sustainably enabled digital freight training as a crucial factor. In the same year, Orji et al., (2020b) presented another study in which training facilities were the most important factor in blockchain implementation.

Table 4:8 Sensitivity analysis

Factors	ANN 1	ANN 2	ANN 3	ANN 4	ANN 5	ANN 6	ANN 7	ANN 8	ANN 9	ANN 10	Normalized Importance	Rank
TI1	0.05	0.05	0.09	0.05	0.02	0.03	0.05	0.03	0.04	0.08	52.84	9
TI2	0.01	0.07	0.02	0.05	0.04	0.08	0.09	0.06	0.10	0.03	61.26	5
TI3	0.06	0.04	0.06	0.02	0.05	0.06	0.02	0.03	0.05	0.11	54.73	7
TI4	0.04	0.02	0.01	0.02	0.02	0.08	0.03	0.03	0.07	0.08	43.81	15
TI5	0.02	0.09	0.03	0.06	0.06	0.03	0.01	0.02	0.06	0.02	43.86	14
O1	0.02	0.01	0.02	0.04	0.03	0.07	0.05	0.01	0.06	0.03	36.82	17
O2	0.02	0.05	0.08	0.04	0.03	0.06	0.01	0.05	0.05	0.02	45.75	13
O3	0.06	0.09	0.02	0.09	0.05	0.05	0.10	0.10	0.07	0.03	72.73	4
O4	0.04	0.06	0.02	0.04	0.04	0.03	0.06	0.05	0.08	0.01	48.81	10
O5	0.16	0.08	0.05	0.07	0.13	0.05	0.03	0.07	0.03	0.09	83.57	2
I1	0.09	0.06	0.11	0.06	0.09	0.02	0.10	0.10	0.07	0.04	82.00	3
I2	0.03	0.01	0.08	0.01	0.04	0.04	0.02	0.02	0.02	0.07	36.15	18
I3	0.03	0.06	0.06	0.06	0.02	0.09	0.03	0.11	0.01	0.03	55.25	6
S1	0.06	0.03	0.02	0.08	0.08	0.04	0.05	0.04	0.02	0.03	47.63	12
S2	0.03	0.03	0.06	0.03	0.06	0.07	0.03	0.04	0.07	0.07	52.91	8
S3	0.11	0.15	0.12	0.10	0.08	0.02	0.14	0.11	0.02	0.06	100.00	1
S4	0.01	0.02	0.02	0.09	0.02	0.02	0.07	0.05	0.02	0.05	39.70	16
S5	0.04	0.02	0.03	0.01	0.05	0.11	0.05	0.02	0.10	0.02	47.89	11

Initial Investment Cost (O5) represents another critical consideration in BCT adoption. While the upfront costs may seem daunting, closer collaboration with blockchain service providers and the development of suitable implementation models can help mitigate financial barriers. By optimizing the advantages of BCT for MFT operations, organizations can recoup initial investments and achieve long-term cost savings, thereby enhancing economic sustainability. Despite the perceived high initial costs of BCT adoption, its subsequent benefits can effectively recoup these expenses over time (Shardeo et al., 2020).

Trust over Digital Technology (I1) emerges as a cornerstone for fostering transparency and trust within the maritime industry. Blockchain's inherent features of traceability and transparency enhance trust among stakeholders, streamlining operations and improving efficiency (Kapnissis et al., 2022). By infusing transparency into the maritime supply chain, blockchain minimizes the need for searching trusted partners, ensuring worry-free transactions and decentralized operations (Cholewa & Shanmugam, 2017). This not only enhances operational efficiency but also strengthens relationships across the industry.

Furthermore, blockchain's attributes of traceability and transparency contribute to environmental sustainability within the maritime sector. By facilitating real-time communication and scheduling, blockchain minimizes idle time at ports, reducing fuel consumption, emissions, and ship dwell time. This aligns with broader efforts to mitigate environmental impact and promote sustainability in maritime freight operations.

Security and privacy is the fourth-ranked factor in the analysis. The maritime freight industry is very much concerned about their essential business information like freight details, suppliers, etc. (Balci & Surucu-Balci, 2021). Consequently, organizations seek assurances in security and privacy, attributes that can be fulfilled through the inherent security features of blockchain technology offering a promising solution to these challenges. Blockchain's decentralized and immutable ledger ensures data integrity and confidentiality, mitigating the risk of unauthorized access and cyber-attacks. By providing secure and tamper-proof data exchange, blockchain enhances trust among stakeholders and safeguards confidential business information. Furthermore, blockchain's transparency features enable controlled access to operational information, addressing concerns about loss of control while maintaining data privacy.

The perceived benefits of BCT, ranked 5, hold significant weight in industry circles. As enterprises become familiar with the wide array of advantages offered by blockchain, rapid adoption becomes increasingly likely. These advantages span various aspects, revolutionizing business operations and increasing efficiency. BCT promises heightened productivity through process streamlining and automation, coupled with enhanced security and transparency. It enables seamless collaboration across organizational boundaries, fostering innovation and agility. Ultimately, disseminating knowledge of these benefits can expedite adoption and unleash BCT's full potential across industries.

4.2 Interrelationships among the determinants influencing Blockchain adoption

Our study aims to identify and categorize the various factors influencing blockchain adoption in maritime logistics. We prioritize these factors based on their weightage and assess the individual impact of each factor on the adoption process. To achieve a comprehensive understanding, we analyze and quantify the cause-effect relationships among the identified factors, determining how they influence one another in the context of blockchain adoption. This interconnected approach will not only highlight the critical determinants of successful implementation but also provide valuable insights into the dynamics of blockchain integration within the maritime logistics sector. By examining these relationships, we hope to develop a clearer framework that stakeholders can use to facilitate and enhance blockchain adoption effectively.

This study has considered the three-phase integrated methodology to understand and establish the relationship among the blockchain adoption factors in the maritime freight enterprise. The Delphi technique is used in the first step to discover and finalize the blockchain adoption factors for managing maritime operations through expert input. Following that, the Grey DEMATEL approach is used to capture the cause-effect linkages among the factors and in the final step, the ANP method is used to capture overall preferences among the factors. Figure 4:5 is showing the framework of Grey-DANP method.

4.2.1 Technology-organization-environment (TOE) framework

The TOE framework was created by De Pietro, Wiarda and Fleischer in 1990 and is primarily used for the adoption of technological advancements (De Pietro, 1990). The theoretical framework is based on organisational, environmental, and technological aspects that have a substantial impact on the adoption issue (Orji et al., 2022b). The technological dimension refers to the impact of technological characteristics on blockchain adoption in maritime logistics. The organisational dimension focuses on the firm characteristics and resources, such as firm size, degree of centralisation, and complexity of its managerial structure which can actually make an impact on the adoption procedure. The environmental factor is related to external factors which include government policies, competition, stakeholder pressure, and market uncertainty.

The diffusion of innovation (DOI) theory (Rogers, 1983) is one of the popular theories in understanding at what rate the innovative technologies spread in a social system. Relative advantage, compatibility, complexity, trialability, and observability are the common technological features that can be considered as antecedents in the adoption process (Wang et al., 2010). Roger (1983) also emphasised three factors, including leader characteristics, and internal and external organisational characteristics. The internal and external organisational characteristics refer to the firm characteristics and environmental factors of the TOE work respectively. Thus, the TOE framework is consistent with the DOI theory or vice versa.

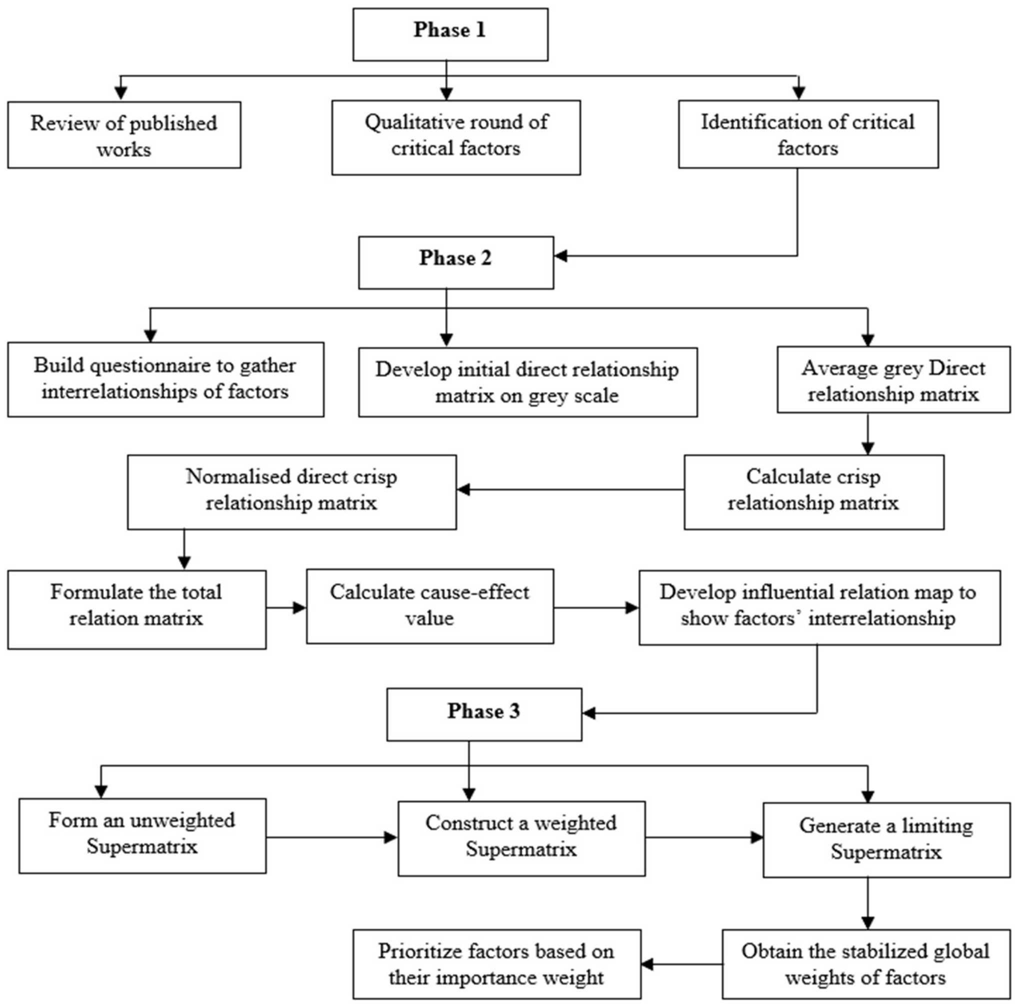

Figure 4:5Flowchart of Grey-DANP

- ***The crucial factors of blockchain implementation in maritime freight enterprises***

  On the basis of a comprehensive review of the relevant literature, and the opinions of industry professionals, a total of 22 factors (shown in Table 4:9) have been identified. The selection procedure for the factors has been elaborated in the sub-section 3.2.

Table 4:9 List of factors to blockchain implementation in maritime freight enterprises

TOE Dimensions	Factors	Description	References	TOE Dimensions
Organizational Factors	**D1**	Support from Senior Management	It is described as the capacity of senior executives to provide guidance, resources, and requirements both before and after the maritime freight transportation company purchases blockchain technologies.	(Zhou et al., 2020)
	D2	Proactive Information Sharing Willingness	Many companies consider their data as a competitive advantage and hence are reluctant to disclose important information.	(Balci & Surucu-Balci, 2021)
	D3	Availability of training facilities for sustainability and blockchain technology both	It makes sure that the workforce has access to the right training resources to facilitate the use of blockchain technologies and sustainability within the maritime logistics sector.	(Orji et al., 2020b)
	D4	Organizational culture	The way an organization responds to outside influences and makes tactical business judgements is impacted by its organizational culture.	(Yang, 2019)
	D5	Reliability and trust	Another key element for blockchain implementation is its promise of dependability.	(Zhou et al., 2020)
	D6	Infrastructural facility	It makes ensuring that existing technologies are supported and capable of meeting the needs of the current infrastructure.	(Orji et al. 2020b)

	D7	The capability of human resources	It guarantees that specialists in maritime freight logistics are qualified to guarantee the effectiveness of blockchain technologies.	(Orji et al., 2020b)
Technological Factors	**D8**	Accessibility	This indicates the necessity of having an adequate number of blockchain solution providers to effectively tackle the challenges faced by client companies.	(Zhou et al., 2020)
	D9	Blockchain Standardization	It establishes technological, operational, and security standards for the blockchain ecosystem and intends to ensure blockchain solution interoperability.	(Balci and Surucu-Balci, 2021)
	D10	Data ownership and control	It refers to the rights and duties of blockchain network-generated and managed data.	(Balci and Surucu-Balci, 2021)
	D11	Scalability	Existing systems need to be scalable across their supply chains in order to implement BCT.	(Park, 2020)
	D12	Availability of technology-specific tools	Lack of standard methods, tools, and techniques for measuring the effectiveness of the implementation of blockchain technology.	(Mangla et al., 2017)
	D13	Supplier/Vendor Readiness	It evaluates whether these important stakeholders (supplier/vendor) have the infrastructure, expertise, and methods to integrate and collaborate in a	(Agi and Jha, 2022)

			blockchain-based system.	
	D14	Ease of testing and observation	In fact, it has an impact on whether blockchains are accepted in the sphere of maritime freight logistics.	(Orji et al., 2020b)
	D15	Security and privacy	It makes sure that shared information is essentially safe to prevent manipulation when blockchain technologies are adopted in the maritime freight transportation industry.	(Nguyen et al., 2023)
	D16	Functional benefits	It outlines the anticipated benefits blockchain technologies would bring to the maritime logistics sector.	(Kapnissis et al., 2022)
	D17	Initial investment cost	Initial investment expenses include the availability of finance to cover the significant capital expenditure required to build blockchain technologies for the maritime freight logistics sector.	(Balci & Surucu-Balci, 2021)
Environmental Factors	**D18**	Competitive pressure	The constant need for maritime logistics companies to prove their expertise to stakeholders or investors is known as competitive pressure. This pressure is a result of the maritime freight logistics industry's external environment.	(Yang, 2019)
	D19	Influential Stakeholders pressure	Stakeholder pressure is closely related to the external environment, which characterizes	(Zhou et al., 2020)

			the strong and continual expectations of several stakeholders or investors in the maritime freight logistics sector.	
	D20	Government policy and support	The ability of key government bodies to offer assistance and implement laws and ordinances to promote blockchain acquisition and sustainability in the maritime logistics industry is referred to as government policy and support.	(Wong et al., 2020)
	D21	Market turbulence	Market turbulence, such as the unpredictability or volatility of paying for logistics services, may have an impact on the deployment of blockchains in the maritime freight logistics sector.	(Orji et al., 2020b)
	D22	Social Responsibility and Ethics	This factor includes moral and social issues related to blockchain technology. It involves assessing blockchain's ethical implications, data privacy, environmental sustainability, and responsible business practices during deployment.	(Upadhyay et al., 2021)

4.2.1.1 Technological context

The technological dimension of the TOE model encompasses the internal and external technologies available to a firm, considering their perceived usefulness, compatibility, complexity, and usage. For example, Accessibility pertains to the level of convenience and availability of blockchain solutions, encompassing both the physical infrastructure and user-friendly interfaces enabling firms to access and integrate blockchain into their processes. Simultaneously, scalability plays a pivotal role in driving firm adoption, as businesses are more inclined to embrace blockchain if they believe it can effectively accommodate their growing needs without compromising performance. Technology-specific tools provide firms with the necessary means to navigate and utilise blockchain effectively, ensuring alignment with operational needs and objectives. Ease of testing and observation refers to the user-friendliness and simplicity of experimenting with and monitoring blockchain implementation, compared to alternative solutions. Assurance of data security and privacy acts as a compelling factor, enhancing the adoption of blockchain as a trusted and reliable solution for various business processes.

4.2.1.2 Organisational context

Organisational dimension pertains to the inherent characteristics and capabilities of the organisation. For example, support from senior management encompasses the endorsement, commitment, and active involvement of top management in championing the adoption of blockchain technology. Willingness to share information creates a conducive environment for potential adopters to assess the benefits of blockchain adoption, facilitating informed decision-making and encouraging more firms to embrace this innovative technology. Organisational culture shapes the firm's values, beliefs, and norms, which can either facilitate or hinder the integration of blockchain. The capability of human resources refers to a workforce equipped with the necessary knowledge and skills that can maximise the potential advantages of blockchain, making it a valuable asset for the organisation.

4.2.1.3 Environmental context

The environmental dimension refers to the external factors outside the immediate organisation that can influence the adoption of a technological innovation, such as; Competitive pressure stems from the need for firms to stay competitive in their respective industries. And, influential stakeholders pressure refers to the influence exerted by key stakeholders such as investors, partners, or industry leaders who advocate for the adoption of blockchain technology. Similarly, government policies that provide incentives, regulatory clarity, and financial support for adopting blockchain can enhance its adoption.

4.2.2 Empirical study

In the course of this research, an extensive review of the literature led to the identification of 30 factors related to the implementation of blockchain technology. To refine and assess these factors for their significance in the context of blockchain adoption, a panel of seven experts, each possessing substantial experience in blockchain technology within their respective domains, was assembled. Each expert was informed about the dimensions taken into account (namely; organisational, technological, and environmental considerations) and their contributing aspects, and they all agreed to give complete answers. Subsequently, a Delphi analysis was conducted. Following the Delphi analysis, 18 factors emerged as noteworthy and were chosen for in-depth evaluation.

4.2.2.1 Delphi Method

The purpose of the Delphi method is to get the most reliable consensus from a group of experts. It is characterized as “a method for structuring a group communication process […] to deal with a complex problem”. The Delphi method relies on experts’ judgements, experience, and values. Thus, the first step in the Delphi method is to select the expert because it has a direct impact on the outcomes. The invited experts must be from a diverse variety of fields but must be related to the topic of investigation. Experts from academia and industry are considered for this study. Experts could understand one another’s views in the first round of the questionnaire and modify or adjust their perspectives in the second round to maintain consistency. The panel of experts in this study consisted of seven respondents from both industry and academia, ensuring a diverse and balanced perspective. The industry experts included a Senior Manager with 10 years of experience, a Project Manager with 12 years of expertise, an IT Manager with 8 years of experience, an Export Manager with 11 years of experience, and a Customer Service Manager with 11 years of industry expertise. Additionally, the academic domain was represented by two Senior Professors with 17 and 19 years of experience, respectively. This diverse selection of experts provided a comprehensive and well-rounded evaluation, incorporating both practical industry knowledge and academic insights.

In this study, we follow two steps such as brainstorming the original factors and then narrowing down them to important factors. We consider three rounds of questionnaires to understand the consensus and difference among the expert's opinion. The initial questionnaire is very simple as it consists of open-ended questions to capture the views of experts. The questionnaire consists of three basic questions, corresponding to the first two research questions. To address the first research question, experts are asked to develop a list of factors (at least eight factors) affecting the adoption of the blockchain. The purpose of this question is to generate a list of factors under the technology, organization, and environment category. In the second question, experts are requested to identify the strategies to manage those adoption factors. The third question is to capture the importance of each factor listed in the first question. In the third question, experts are asked to briefly explain (in three to four sentences) the importance of each factor. These explanations facilitate us to understand the experts' views and also reconcile their opinions. We sent the questionnaire to each expert and analyzed the results. While analyzing the results, we removed the duplicate factors and developed a consolidated list of a total of 22 factors. This consolidated list is then sent to the experts to narrow down the list. Each expert is requested to consider at least fifteen factors from the list. We consider only those factors which are selected by over 50% of experts i.e., 18 factors. A description of the steps involved in the Delphi study is shown in Figure 4:6.

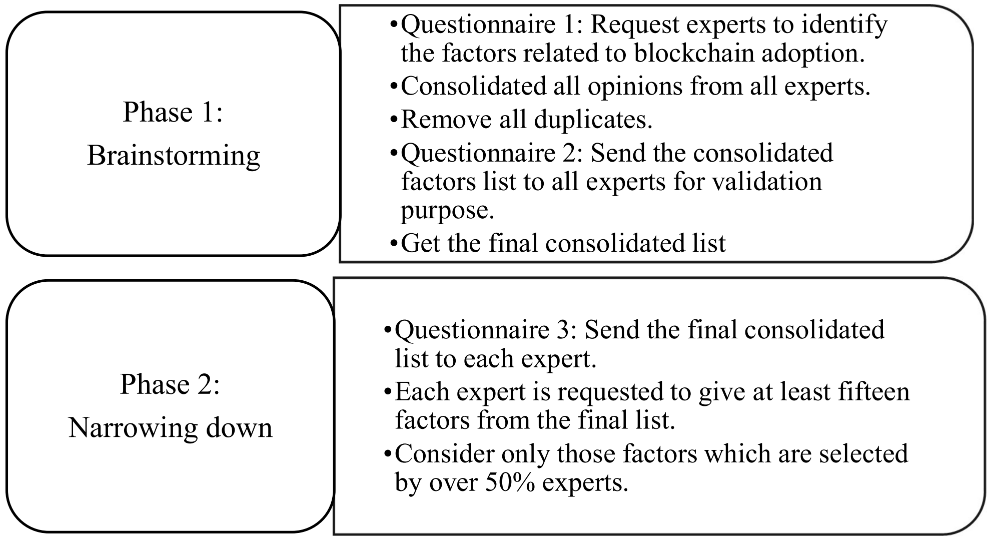

Figure 4:6 Steps involved in the Delphi method.

According to steps mentioned in section 3.3.1 of chapter 3, we prepared a questionnaire with a Likert scale ranging from 'no effect' to 'very strong effect' was distributed to four industry experts for collecting inter-relationships of factors, as shown in Table 4:10. Based on the greyscale, the experts' opinions are compiled in pairs. As a result, distinct 18 by 18 matrices are obtained. The initial grey relational matrix has been prepared.

Table 4:10 Grey Linguistics Scale

Linguistic Terms	**Normal Value**	**Grey Range**
No Influence (N)	0	[0.0,0.1]
Very Low Influence (VL)	1	[0.1,0.3]
Low Influence (L)	2	[0.2,0.5]
Medium Influence (M)	3	[0.4,0.7]
High Influence (H)	4	[0.6,0.9]
Very High Influence (VH)	5	[0.9,1.0]

Thereafter, we compute the compute the aggregated grey relational matrix according to equation 3-2 and calculated the crisp matrix from the aggregated matrix based on equations 3-3 to 3-9. The normalised matrix is finally computed based on equation 3-10 and determines the total influence matrix (T). The total influence matrix is shown in

Table 4:11 From the total influence matrix, we determine the overall influence that each factor transmitted and received. The total relational matrix along with prominence and net effect value are shown in Table 4:12

a) ***Technological determinants***

Based on Figure 4:9, we observe the following results: Among the causal category, the Availability of technology-specific tools (D12) demonstrates the highest positive impact with a Ri + Cj value of 7.391, securing the top rank. This indicates that addressing the Availability of technology-specific tools can significantly influence the system positively. Following closely, Initial investment cost (D14) holds the second position with a Ri + Cj value of 6.807, emphasising its dominance over all other determinants. For this determinant to come to fruition, governments and blockchain service providers should pay attention to its high cost. Functional benefits (D13) also present a noteworthy influence, securing the fourth position with a Ri + Cj value of 6.710. Managers and service providers should disseminate the perceived benefits of blockchain among industry personnel so that they can be motivated to adopt it knowing its benefits. Ease of testing and observation (D11) is ranked sixth with a Ri + Cj value of 5.338. Whereas, in the effect category, Security and privacy (D12) ranks third with a Ri + Cj value of 7.195, highlighting their impact. Accessibility (D8) follows with a Ri + Cj value of 6.310, ranking fifth. Lastly, Scalability (D9) ranks seventh with a Ri + Cj value of 5.532, indicating its influence on the system.

The causal diagram is constructed by assessing the impact received and given by the factors. The diagram provides a visual framework to analyse the cause-and-effect relationships among these factors, allowing for a comprehensive understanding of how changes or variations in one factor may influence others. Figure 4:7 shows the cause-effect diagram of factors. The obvious effects will be filtered out using a threshold value of 0.17843. Finally, the total relation matrix, consider as an unweighted supermatrix and transformed into a weighted supermatrix (W), as shown in Table 4:13.

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4.2.3 Results and discussions

This research represents a substantial step forward in our comprehension of the determinants that shape the adoption of blockchain technology within the maritime freight sector. The study is grounded in a robust analytical framework that encompasses the pivotal Technological, Organizational, and Environmental (TOE) determinants, providing a holistic understanding of this multifaceted issue. In the pursuit of greater depth and insight, the investigation leverages the Delphi technique along with the Grey DEMATEL-ANP methodology. Through meticulous scrutiny, this study not only sheds light on the inherent characteristics of these determinants but also unravels their intricate web of causal and effect relationships. This nuanced analysis contributes significantly to the body of knowledge within the field and holds tangible implications for stakeholders in maritime freight enterprises. The rankings, guided by the global weights of these determinants, offer a clear hierarchy of their overall significance in propelling the adoption of blockchain technology within the maritime industry. This research paves the way for a more informed and strategic approach to blockchain implementation, ensuring that the maritime sector can harness the full potential of this transformative technology.

Table 4:11 The Total Influence Matrix

Factor_ID	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15	D16	D17	D18
D1	0.115	0.253	0.191	0.144	0.080	0.185	0.203	0.230	0.171	0.190	0.145	0.181	0.141	0.137	0.144	0.230	0.133	0.106
D2	0.116	0.156	0.109	0.151	0.086	0.119	0.122	0.157	0.112	0.136	0.108	0.142	0.148	0.129	0.155	0.201	0.110	0.087
D3	0.177	0.315	0.146	0.198	0.111	0.212	0.235	0.257	0.184	0.248	0.195	0.216	0.200	0.153	0.221	0.272	0.168	0.170
D4	0.115	0.230	0.128	0.122	0.103	0.118	0.163	0.156	0.138	0.159	0.110	0.176	0.146	0.151	0.164	0.202	0.151	0.105
D5	0.119	0.237	0.116	0.165	0.070	0.117	0.154	0.145	0.115	0.191	0.110	0.166	0.162	0.120	0.181	0.220	0.116	0.128
D6	0.163	0.297	0.187	0.185	0.102	0.137	0.210	0.235	0.200	0.237	0.185	0.240	0.175	0.139	0.171	0.262	0.149	0.112
D7	0.196	0.299	0.179	0.206	0.119	0.174	0.161	0.229	0.155	0.226	0.154	0.222	0.200	0.148	0.185	0.255	0.181	0.135
D8	0.116	0.238	0.123	0.148	0.075	0.113	0.193	0.128	0.172	0.139	0.137	0.168	0.139	0.109	0.126	0.219	0.113	0.087
D9	0.127	0.243	0.145	0.166	0.103	0.132	0.148	0.189	0.103	0.171	0.124	0.196	0.132	0.130	0.137	0.192	0.141	0.113
D10	0.179	0.327	0.212	0.216	0.122	0.199	0.219	0.253	0.198	0.181	0.170	0.265	0.209	0.172	0.221	0.299	0.180	0.155
D11	0.156	0.231	0.118	0.137	0.084	0.181	0.155	0.201	0.137	0.153	0.097	0.194	0.146	0.121	0.133	0.214	0.131	0.102
D12	0.175	0.305	0.160	0.230	0.124	0.183	0.172	0.205	0.182	0.206	0.146	0.174	0.205	0.198	0.222	0.267	0.179	0.120
D13	0.208	0.305	0.176	0.224	0.092	0.184	0.229	0.242	0.172	0.220	0.151	0.249	0.149	0.185	0.190	0.272	0.172	0.121
D14	0.203	0.346	0.206	0.260	0.172	0.228	0.251	0.268	0.198	0.262	0.182	0.270	0.224	0.149	0.251	0.314	0.185	0.169
D15	0.177	0.262	0.159	0.201	0.137	0.167	0.200	0.180	0.136	0.195	0.146	0.210	0.175	0.130	0.138	0.240	0.149	0.139
D16	0.197	0.323	0.211	0.217	0.122	0.199	0.236	0.234	0.158	0.249	0.185	0.239	0.192	0.187	0.218	0.221	0.170	0.165
D17	0.210	0.324	0.194	0.215	0.101	0.214	0.252	0.266	0.162	0.218	0.167	0.250	0.222	0.169	0.216	0.283	0.136	0.128
D18	0.153	0.279	0.195	0.202	0.137	0.177	0.199	0.191	0.148	0.230	0.136	0.184	0.205	0.142	0.190	0.258	0.174	0.101

4.2.3.1 Cause & effect analysis

It is common to come across multiple elements in complicated decision-making problems that either influence some factors (referred to as cause category criterion) or are impacted by other factors (referred to as effect category criterion). Due to the dependence relationships between various factors, it is no longer true that improving any one element or criterion will improve the entire system. It is therefore crucial to identify these dependence relationships in order to recognise the elements in the causal category that can be enhanced to elevate the criteria of the effect category, thereby enhancing the overall system (Govindan et al., 2016).

The effect group consists of factors showing a negative (Ri – Cj) value, suggesting that they are influenced by other factors in the analysis refer to Figure 4:7. The Environmental Factors (ENV) are the most prominent in this group, with a (Ri – Cj) value of −0.7235. This implies that changes in environmental factors are significantly influenced by other factors, particularly those in the cause group. The Organizational Factors (ORG) are also part of the effect group with a (Ri – Cj) value of −0.1457. Lastly, the Technological Factors (TECH) are part of the effect group due to their (Ri – Cj) value of 0.8691, meaning they are affected by other factors more than they cause changes in the system.

In contrast, Organizational Factors (ORG) have the highest influence in the system, as indicated by the highest (R+C) value. It's worth noting that these factors are part of the effect group, signifying that they are susceptible to the influence of other causal elements. Environmental Factors (ENV) have the second-highest influence in the system, with a 7.65 (R+C) value, followed by Technological Factors (TECH).

b) *Organisational determinants*

From Figure 4:8 &Table 4:12, it is evident that all determinants, with the exception of D2, D4, and D7 fall within the effect category. These determinants are ranked as follows: D3, D6, D1 and D5, with values of 6.633, 6.426, 5.882, and 4.572, respectively. The placement of D2, D4, and D7 organisational determinants above the x-axis signifies their causal nature. Moreover, Proactive Information Sharing

Willingness 'D2', and the capability of human resources 'D7' determinants become the first & second highest prominence factors of the effect group, respectively.

c) *Technological determinants*

Based on Figure 4:9, we observe the following results: Among the causal category, the Availability of technology-specific tools (D12) demonstrates the highest positive impact with a Ri + Cj value of 7.391, securing the top rank. This indicates that addressing the Availability of technology-specific tools can significantly influence the system positively. Following closely, Initial investment cost (D14) holds the second position with a Ri + Cj value of 6.807, emphasising its dominance over all other determinants. For this determinant to come to fruition, governments and blockchain service providers should pay attention to its high cost. Functional benefits (D13) also present a noteworthy influence, securing the fourth position with a Ri + Cj value of 6.710. Managers and service providers should disseminate the perceived benefits of blockchain among industry personnel so that they can be motivated to adopt it knowing its benefits. Ease of testing and observation (D11) is ranked sixth with a Ri + Cj value of 5.338. Whereas, in the effect category, Security and privacy (D12) ranks third with a Ri + Cj value of 7.195, highlighting their impact. Accessibility (D8) follows with a Ri + Cj value of 6.310, ranking fifth. Lastly, Scalability (D9) ranks seventh with a Ri + Cj value of 5.532, indicating its influence on the system.

Table 4:12Cause & Effect analysis of factors

Dimensions	Ri	Cj	Ri + Cj	Ri - Cj	Nature	Factors	Ri	Cj	Ri + Cj	Ri - Cj	Nature
Org	4.628	4.774	9.402	-0.146	Effect	D1	2.980	2.902	5.882	0.078	Cause
						D5	2.345	4.968	7.313	-2.623	Effect
						D8	3.678	2.955	6.633	0.722	Cause
						D16	2.636	3.388	6.025	-0.752	Effect
						D17	2.632	1.904	4.572	0.691	Cause
						D2	3.387	3.039	6.426	0.347	Cause
						D11	3.426	3.501	6.927	-0.075	Effect
Tech	3.816	2.947	6.764	0.869	Cause	D4	2.544	3.766	6.310	-1.223	Effect
						D6	2.691	2.841	5.532	-0.150	Effect
						D10	3.777	3.614	7.391	0.163	Cause
						D3	2.691	2.647	5.338	0.044	Cause
						D7	3.453	3.742	7.195	-0.289	Effect
						D13	3.541	3.169	6.710	0.372	Cause
						D14	4.138	2.669	6.807	1.470	Cause
Env	3.462	4.185	7.647	-0.723	Effect	D15	3.142	3.266	6.408	-0.123	Effect
						D12	3.723	4.420	8.143	-0.697	Effect
						D9	3.727	2.739	6.467	0.988	Cause
						D18	3.301	2.244	5.545	1.057	Cause

d) ***Environmental determinants***

Four determinants were identified under this dimension, out of which two were categorised as causal factors, while 2 factors have been classified as effect factors. The causal factors' ranking demonstrates that Government policy and support 'D17' is the determinant with the highest prominence value with a value of 6.467, followed by the Market turbulence 'D18' as the second highest influencing determinant in the cause group with a prominence value of 5.545, meaning it dominates all other factors.

Likewise, the determinant with the highest prominence value in the effect group is Influential Stakeholders pressure 'D16' with a prominence value of 8.14. Therefore, the stakeholders of the maritime freight enterprises should motivate the top management of the company to develop a sustainable and efficient environment for the industry through blockchain adoption. Likewise, Competitive pressure 'D15' became the second highest prominence factor of the effect group. Figure 4:10 shows a pictorial view of these factors grouped into cause-and-effect groups.

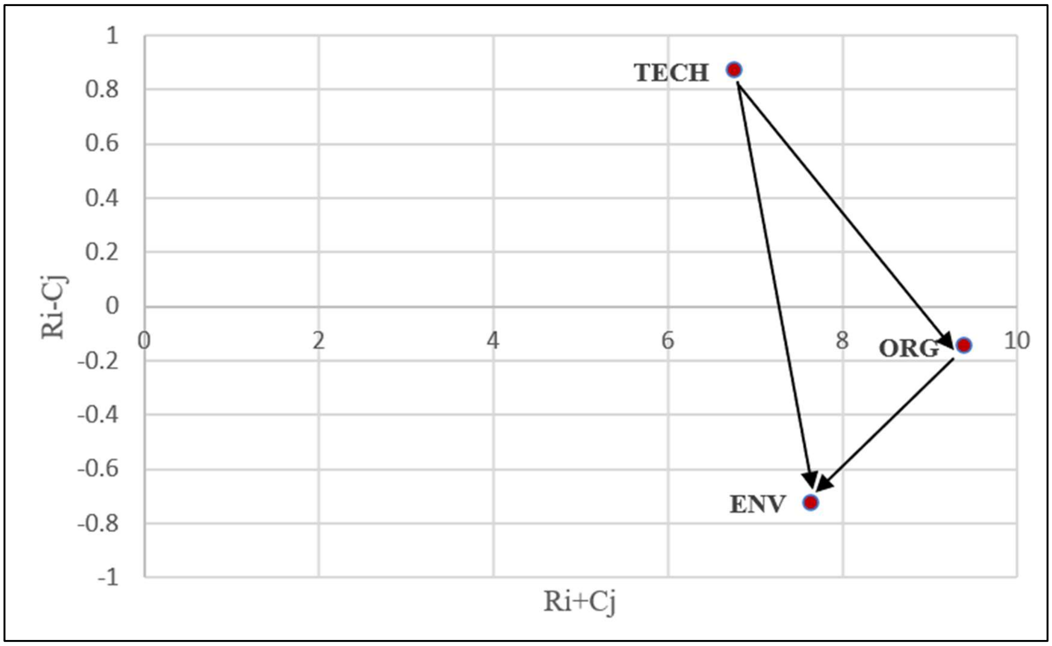

Figure 4:7 Influential Relation Diagram of dimensions

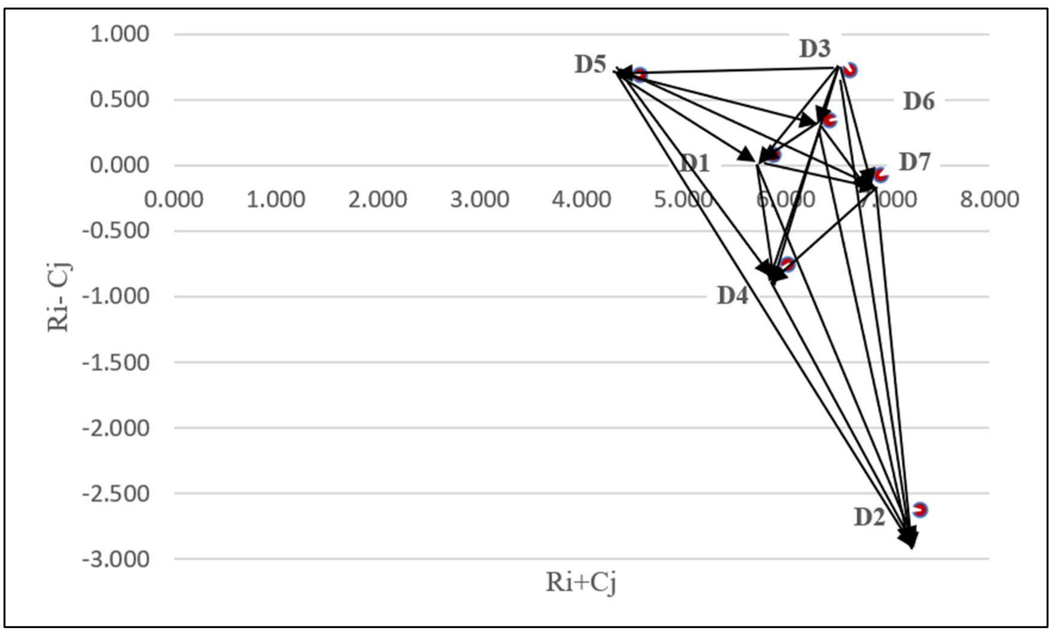

Figure 4:8 Influential Relation Diagram of Organizational Determinants

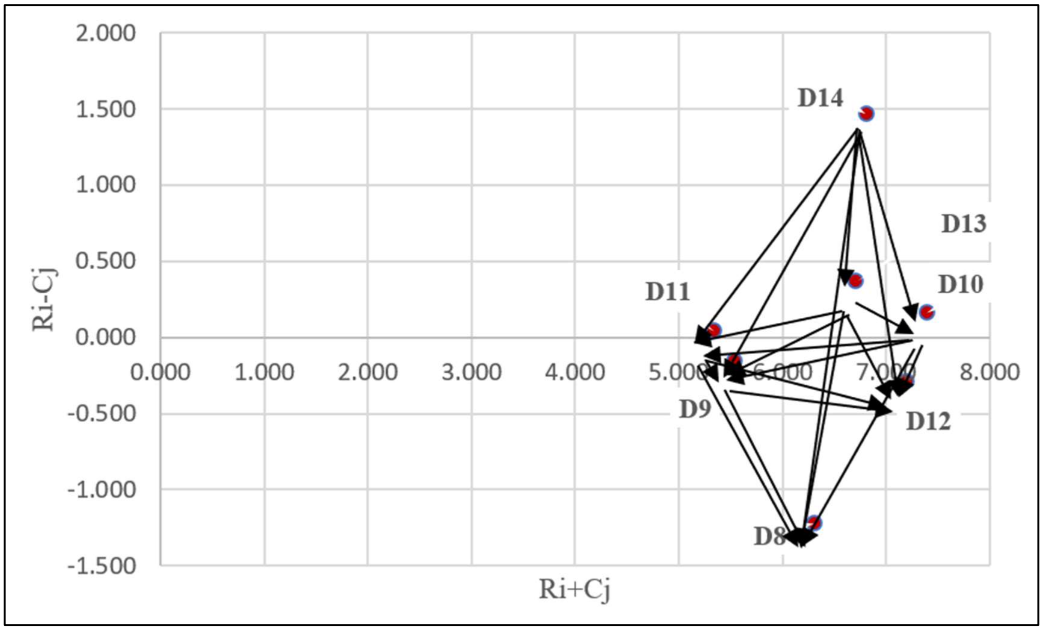

Figure 4:9 Influential Relation Diagram of Technological Determinants

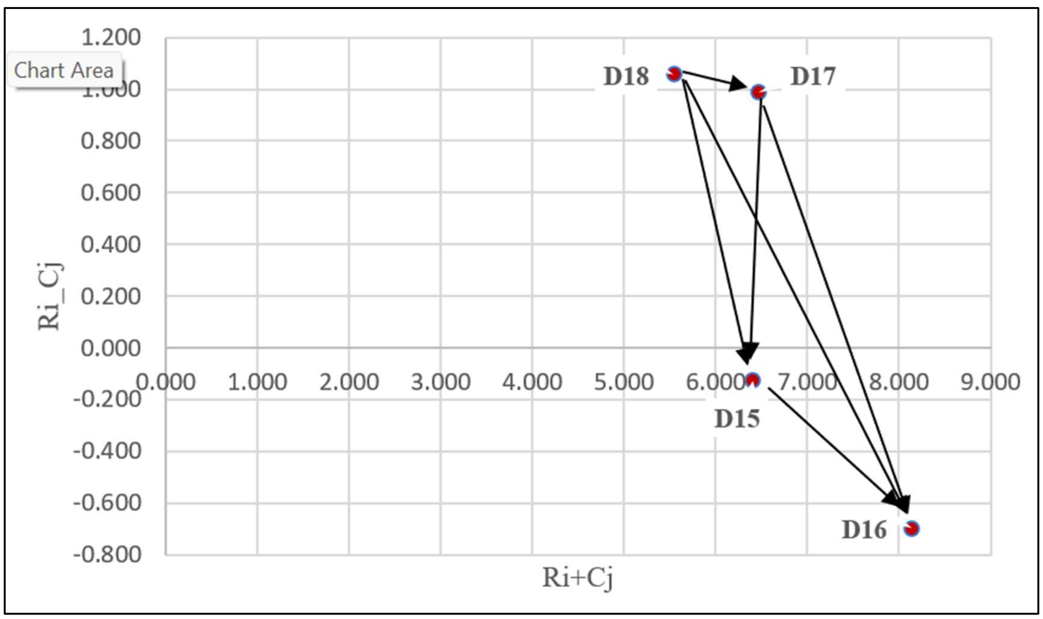

Figure 4:10 Influential Relation Diagram of Environmental Determinants

4.2.3.2 Correlation among determinants

The correlation between the factors, as determined by the DEMATEL method, exhibits a complex interplay of influences and responses within the system. The analysis indicates a dynamic network of relationships where certain factors directly influence others, and, in turn, some factors are more sensitive to these influences. The determinants with high prominence (Ri + Cj) value are significant causal or effect determinants. In this sense, the causal determinants with high prominence value are D10 > D14 > D13 > D8 > D9 > D2 etc. These determinants indicated that these determinants have a significant causal influence within the system. It implies that these determinants play a crucial role in initiating actions or changes in other determinants. These causal factors are connected with the affected factors, including D12 > D5 > D7 > D11 > D15 > D4 > D16 with high prominence value, which display a heightened responsiveness to the influences of the causal factors.

This complex correlation highlights the intricate nature of the system and underscores the importance of understanding the dynamics between these determinants for effective decision-making and system optimisation. It suggests that changes or interventions in the causal factors can have a cascading impact on the affected factors, potentially leading to system-wide effects. This insight can guide strategies for managing and improving the system while minimising unintended consequences. The global weights listed in Table 4:13 are displayed for each determinant. These factors are ranked according to these weights. In which Initial Investment Cost, Availability of technology-specific tools, organisational culture, reliability, and trust, ‘

Stakeholders’ pressure, Government policy and support, and Availability of training facilities are the top five factors. The study conducted by Zhou et al. (2020) also supports the determinant ‘Initial Investment Cost’, followed by Zeng et al. (2021) research on ‘Availability of technology-specific tools.’ In order for the third rank determinant like ‘Government Policy and Support’ to come to fruition, policymakers should come up with some policies regarding blockchain adoption that can help maritime freight enterprises through the government. And managers should provide timely training facilities to make employees aware of blockchain technology, so that the technology can be implemented successfully in maritime freight enterprises.

Table 4:13 Global Weights and Rankings

Factors	Global Weights	Ranking
D1	0.05136	12
D2	0.04103	18
D3	0.06346	5
D4	0.04622	15
D5	0.04546	16
D6	0.05796	9
D7	0.06006	7
D8	0.04356	17
D9	0.04665	13
D10	0.06529	2
D11	0.04636	14
D12	0.06006	7
D13	0.06094	6
D14	0.07142	1
D15	0.05473	11
D16	0.06495	3
D17	0.06385	4
D18	0.05739	10

4.2.3.3 Sensitivity analysis

When delving into the outcomes of this research, several pivotal questions arise. These questions centre around the influence of decision-maker selection on our findings, the magnitude of this influence, the role played by personal bias in data variation, and the means to ascertain the credibility of our results, ensuring they remain unaffected by personal bias. To address these questions, we conducted a sensitivity analysis, a well-recognised approach, as advocated by Singh et al. (2021), for assessing the stability of results when input values undergo marginal variations. As human decisions constitute the primary input in our study, employing a sensitivity analysis becomes instrumental in scrutinising and validating our results, in alignment with Singh et al. (2022).

Our analysis highlights the utmost importance of the Initial investment cost determinant in all four cases. We conducted a sensitivity analysis by incrementally adjusting the weight of experts' initial matrices refer to Table 4:14 (Kamat et al., 2022; Sahu et al., 2023; Seker & Zavadskas, 2017). Sequentially, a higher weight was assigned to one expert while the remaining experts were given equal weightage. By systematically rolling the weights across all four experts, we recorded the outputs.

The results of our sensitivity analysis are visually depicted in Figure 4:11, demonstrating how changes in the weightage of experts' influence shifts in determinants' global weights. Approximately, all of the determinants consistently maintain their global weights across multiple trials, resulting in overlapping lines in Figure 4:11. This comprehensive analysis validates that adjustments in experts' weightage do not impact the determinants' global weights, underscoring the absence of biases in the analysis outcomes.

Table 4:14 Weights Assigned During Sensitivity Analysis

Expert's	Case 1	Case 2	Case 3	Case 4
Expert 1	0.40	0.20	0.20	0.20
Expert 2	0.20	0.40	0.20	0.20
Expert 3	0.20	0.20	0.40	0.20
Expert 4	0.20	0.20	0.20	0.40

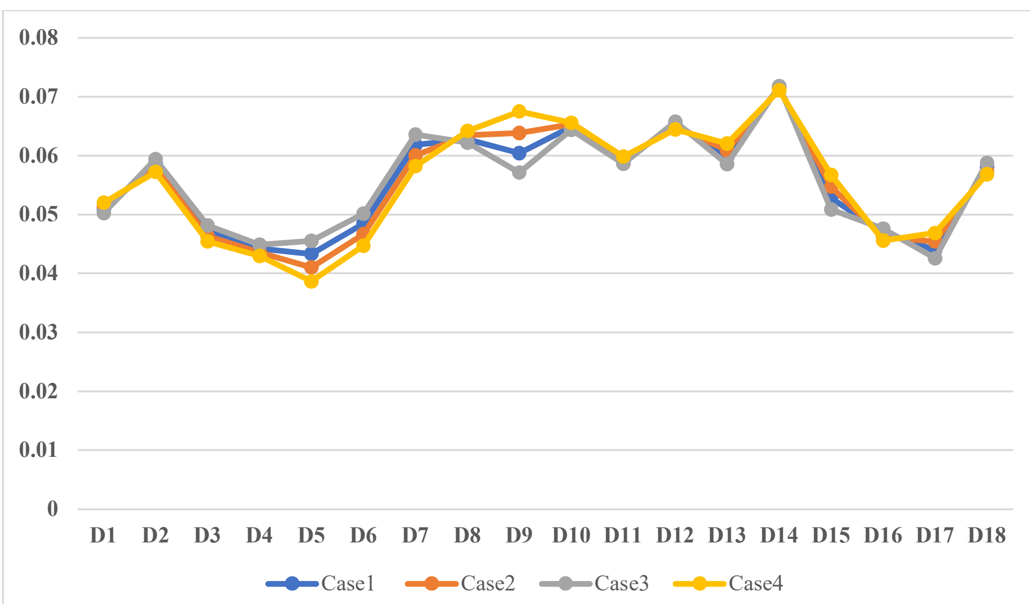

Figure 4:11 Global weights of determinants during sensitivity analysis

4.3 Constraints to the adoption of Big data and AI

This work focuses on identifying the constraints hampering the execution of Big Data and Artificial Intelligence (AI) in the maritime freight industry. To achieve this, we prioritize these barriers based on their relative importance and impact using the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and the Preference Ranking Organization Method for Enrichment Evaluations II (PROMETHEE II) approach. By employing these methods, we aim to rank the constraints & gain a clearer understanding of their significance. This approach will help us provide actionable insights and strategies to overcome the challenges associated with implementing these advanced technologies in the maritime sector.

The proposed integrated framework Fuzzy AHP-PROMETHEE II follows a total of 3 steps consisting of 7 steps. These are listed below; Data gathering comes first, AHP application and PROMETHEE II come last.

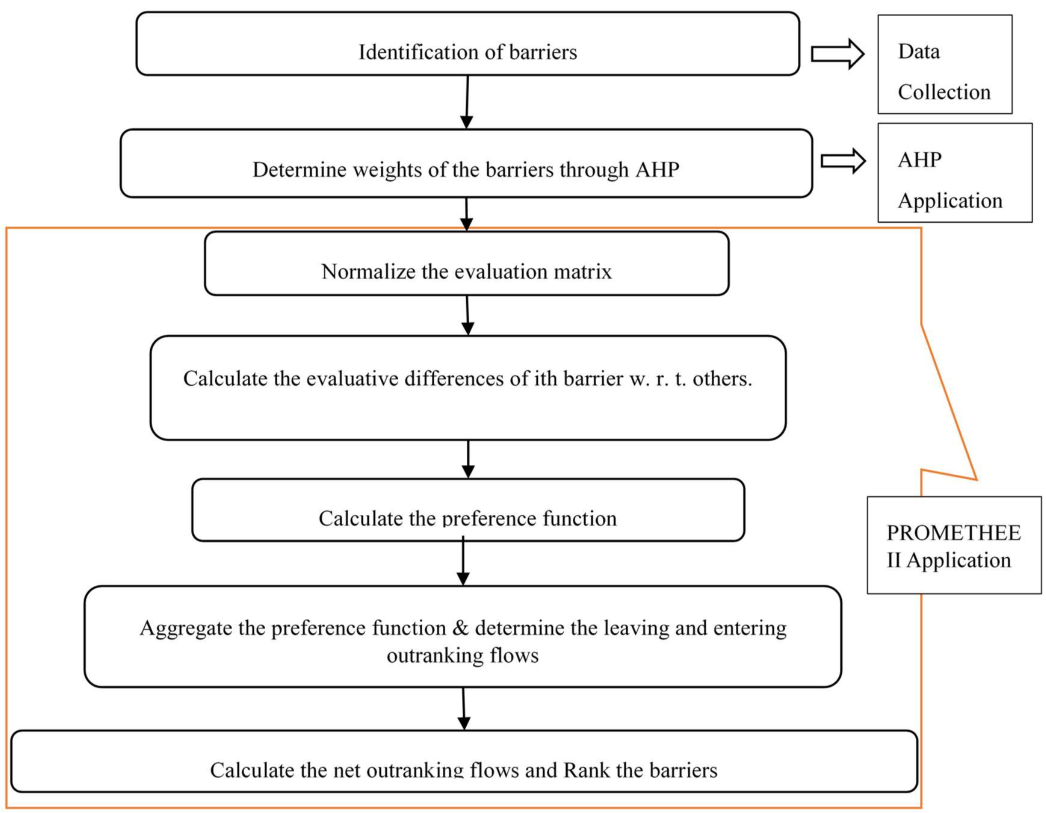

Figure 4:12 Framework of FAHP-PROMETHEE II

4.3.1 Data Gathering

An understanding of the barriers hindering the adoption of Big Data and AI in maritime freight transport has been gained through previous research. To ensure the relevance of these constraints in the case study, insights were gathered from experts representing various stakeholders, such as academic researchers specializing in transportation and supply chain, as well as professionals from maritime companies. Three specialists were selected from each group; all experts had at least eight years of work experience in their respective fields. Each expert was informed about the identified constraints and willingly provided their responses within 3 weeks. The demographic profile of experts is provided in Appendix A. In order to evaluate the interdependence of the restrictions and identify their impact on the adoption of the two technologies, a survey was carried out using a scale ranging from "no influence" to "very high influence," as shown in Table 4:15. The results of the survey are presented in the following table. Table 4:16 shows all the constraints hampering Bigdata and AI adoption in the maritime freight industry.

Table 4:15 Scale for fuzzy AHP method

Linguistic scale for importance	**Corresponding Fuzzy number**	**TFN (Triangular fuzzy number) (l, m, u)**
Just equal (JE)	0	(1, 1, 1)
Equal Importance (EImp)	1	(1, 1, 3)
Weak importance (WImp)	3	(1, 3, 5)
Essential or strong Importance (SImp)	5	(3, 5, 7)
Very strong importance (VSImp)	7	(5, 7, 9)
Extremely preferred (ExImp)	9	(7, 9, 9)
		Reciprocal of above $\boldsymbol{M^{-1} = (\frac{1}{u}, \frac{1}{m}, \frac{1}{l})}$

- ***The crucial constraints to Bigdata & AI adoption in maritime freight industry***

On the basis of a comprehensive review of the relevant literature, and the opinions of industry professionals, a total of 20 constraints (shown in Table 4:16) have been identified. The selection procedure for the factors has been elaborated in the data gathering section.

Table 4:16 List of constraints hampering Bigdata and AI adoption in the maritime freight industry.

Notations	Constraints	Description	References
C1	Susceptibility to cyber threats	Apprehensions regarding data breaches, unauthorized access, and manipulation of vital systems discourage stakeholders from adopting these digital technologies. The possible consequences of cyberattacks, such as disruption of operations, compromise of sensitive data, and reputational harm, generate a sense of insecurity and reluctance to completely leverage big data and AI solutions.	(Ben Farah et al., 2022)
C2	Limited exposure to data interpretation methods	Without adequate knowledge and experience in analysing and interpreting complex data sets, it may be difficult for stakeholders to fully realise the potential of big data and AI technologies.	(World trade organisation, 2022)
C3	Absence of a regulatory framework	Stakeholders are faced with concerns around data privacy, security, ethical use, and compliance obligations in the absence of defined rules and regulations. Without a legislative framework, investment is discouraged and the creation of standardised procedures is hampered, which prevents the general adoption of these technologies.	(Johansson et al., 2021; Kumar et al., 2022a)
C4	Inability to make big data usable for the end user	If stakeholders cannot successfully extract insights and turn them into meaningful information, the benefits of enormous amounts of data remain unexplored. This constraint makes it difficult to make decisions, prevents operational advancements, and prevents big data and AI technologies from reaching their full potential.	(Zhang & Lam, 2019)
C5	Inconsistent data quality	The accuracy and dependability of analytical models and algorithms employed in big data and AI applications are compromised by	(Johansson et al., 2021; Nguyen et al., 2023)

		inconsistent data quality. Inaccurate, out-of-date, or incomplete data might result in erroneous inferences and poor judgment.	
C6	Uncertainty about technology's initial costs and potential benefits	Concerns regarding the financial ramifications and return on investment may cause stakeholders to hesitate to invest in these technologies. Decision-makers may hesitate to invest resources in adoption if they do not have a clear knowledge of the costs and benefits.	(Kim & Schröder-Hinrichs, 2021)
C7	Limited executive bandwidth amid a competitive market	Executives and decision-makers frequently struggle with time constraints and competing priorities, making it difficult to concentrate on adopting and managing big data and AI efforts.	(Etemadi et al., 2021; Zhang and Lam, 2019)
C8	Lack of cross-enterprise technology harmonization	The lack of standardized technology platforms and interoperability restricts data's seamless sharing and integration in an ecosystem with numerous players and various systems.	(Kallisch et al., 2023)
C9	Decentralized data storage	It is challenging to efficiently gather, analyze, and extract insights from data stored across numerous distant places and systems.	(Lambrou et al., 2019; Sundarakani et al., 2021)
C10	Requirement of Architecture for Large Dataset	Robust infrastructure and storage capacities are required due to the industry's enormous volume, velocity, and variety of data generation. Without a suitable architecture, processing and analyzing massive datasets becomes difficult, limiting the possibility of obtaining insightful data and successfully using AI algorithms.	(Agbehadji et al., 2020; Sarabia-Jácome et al., 2019)
C11	The inability of current database software to load data fast enough	The current database software may find it difficult to effectively handle the volume and velocity of data as the industry produces enormous amounts of data in real time. This constraint prevents rapid data processing, analysis, and decision-making, which limits the use of big data and AI technologies to their full potential.	(de la Peña Zarzuelo et al., 2020; Wright et al., 2019)
C12	Poor coordination	Lack of efficient coordination and collaboration prevents data sharing and integration in a complex maritime	(Jović et al., 2020; Tijan et al., 2021)

	among relevant parties	freight ecosystem comprising numerous players, including shipping lines, ports, and logistics providers. This causes data sets to become fragmented, restricts data interaction, and makes it challenging to create integrated big data and AI solutions.	
C13	Lack of data source	Stakeholders have difficulty efficiently utilizing big data analytics and AI algorithms without access to comprehensive and high-quality data. The extraction of significant insights and the capacity to make educated decisions are hampered by limited or fragmented data sources.	(Agbehadji et al., 2020; Shivaprakash et al., 2022)
C14	Lack of encouragement for sharing information	This absence of information sharing hinders collaboration, limits the accuracy and completeness of analytics, and impedes the industry's ability to fully exploit the potential of big data and artificial intelligence technologies.	(Zhou et al., 2020)
C15	High time consumption to set up the structure using big data analytics	Due to their complexity and scope, implementing big data analytics solutions requires significant time and resources for infrastructure setup, data integration, and algorithm development. This lengthy realization period delays benefits acquisition and may discourage stakeholders from adopting big data.	(Munim et al., 2020)
C16	Lack of executive sponsorship	Without significant backing and endorsement from senior executives, organizations would have conflicts in allocating funds, procuring investments, and promoting adoption.	(Sharma et al., 2022)
C17	Limited availability of data-proficient staff	The successful implementation of these technologies requires specialists with the ability to collect, analyse, and interpret large datasets efficiently.	(Trelleborg Marine Systems, 2018; Zhou et al., 2020)
C18	Absence of guidelines for specific tasks	Without clear-headed principles and best practices, stakeholders may have difficulty navigating the implementation of these technologies within specific tasks and processes.	(Munim et al., 2020)

C19	Data falsification	The integrity and dependability of the data are compromised by misreporting of data, which compromises the precision of analytics and decision-making.	(Trelleborg Marine Systems, 2018)
C20	Perceived expenses outweigh the anticipated advantages	Stakeholders may be discouraged from pursuing adoption due to the projected high costs associated with adopting and maintaining big data and AI technologies.	(Gusc et al., 2022; Misra et al., 2020)

4.3.2 Emperical study

4.3.2.1 Determination of weights

The proposed framework includes two essential steps: allocating weights to each risk and evaluating their scores. This progression is illustrated in's sequential structure. Combining these two components yields the rank of the factors.

As shown in Table 4:15, this framework collects inputs from specialists through linguistic expressions. According to Figure 4:123, each input parameter is categorized into five semantic explanations with membership values.

The first stage involves assigning weights using fuzzy pairwise comparisons among the criteria. The pairwise comparison matrix is constructed based on expert opinion and solved using the fuzzy AHP technique, as shown in equation 3-15.

After that, with the help of the succeeding equation, the geometric means of these values are calculated to obtain a consensus pairwise comparison matrix. Following the remaining equations, the weights for all other sub-criterion are established, & depicted in Table 4:17.

4.3.2.2 Assignment of ranks

The final criteria ranking has been assigned using the PROMETHEE II method, considering the previously calculated criteria weights obtained through the Fuzzy Analytic Hierarchy Process (AHP).

The decision matrix has been normalized using Equations 3-21, and the preference functions for all pairs of criteria have been calculated using Equations 3-23 and 3-24.

In addition, the values of the aggregated preference function were determined using equation 3-25 for these paired criteria. The leaving and entering flows for various criteria have been computed using Equations 3-26 and 3-27 and are shown in Table 4:18. The net outranking flow values for each criterion and their relative rankings have been determined using equation 3-28 and are presented in Table 4:18. Furthermore, the criteria have been arranged in descending order based on their net outranking flow values. This showcases the applicability and usefulness of the PROMETHEE II method for solving intricate decision-making challenges within the maritime context.

4.3.3 Results & Discussion

The analysis offers insights into the overall assessment of the criteria and also delves into specific evaluations for each criterion at their respective levels.

4.3.3.1 Analysis of weights

The weighted analysis conducted for the second-level constraints reveals valuable insights into their relative importance within the maritime freight transport industry (refer to Table 4:17 & Figure 4:13). The highest relative weight criterion, "Limited exposure to data interpretation methods" holds a significant weight of 0.0594, indicating its strong influence on the overall resistance assessment. Similarly, other most significant constraints of big data adoption in the maritime freight industry, in descending order of their influence, are "Absence of a regulatory framework" (weight: 0.0586), "Susceptibility to cyber threats" (weight: 0.0583), "Inability to make big data usable for the end user" (weight: 0.0546), The ranking of the remaining second-level constraints based on their weights follows as; C8 > C6 > C7 > C11 > C9 > C13 > C14 > C12 > C15 > C16 > C17 > C18 > C20, and C19 reflecting their respective levels of importance in driving the overall ranking of the constraints within the resistance assessment framework.

The forthcoming section will delve into a detailed analysis of the constraints based on their respective rank, providing a comprehensive understanding of their characteristics and potential impacts.

Table 4:17 Weights of the barriers using the fuzzy AHP method

Constraints	Fuzzy Weights	Weights
C1	(0.0512, 0.0586, 0.0661)	0.0583
C2	(0.0522, 0.0599, 0.0670)	0.0594
C3	(0.0520, 0.0589, 0.0660)	0.0586
C4	(0.0473, 0.0550, 0.0625)	0.0546
C5	(0.0463, 0.0538, 0.0610)	0.0534
C6	(0.0463, 0.0535, 0.0609)	0.0532
C7	(0.0461, 0.0524, 0.0595)	0.0524
C8	(0.0480, 0.0544, 0.0617)	0.0544
C9	(0.0427, 0.0493, 0.0560)	0.0490
C10	(0.0410, 0.0467, 0.0546)	0.0472
C11	(0.0434, 0.0494, 0.0571)	0.0497
C12	(0.0408, 0.0472, 0.0549)	0.0474
C13	(0.0423, 0.0489, 0.0560)	0.0488
C14	(0.0422, 0.0483, 0.0554)	0.0484
C15	(0.0407, 0.0470, 0.0547)	0.0472
C16	(0.0394, 0.0447, 0.0521)	0.0451
C17	(0.0394, 0.0444, 0.0524)	0.0451
C18	(0.0390, 0.0438, 0.0518)	0.0446
C19	(0.0363, 0.0414, 0.0473)	0.0414
C20	(0.0364, 0.0424, 0.0480)	0.0420

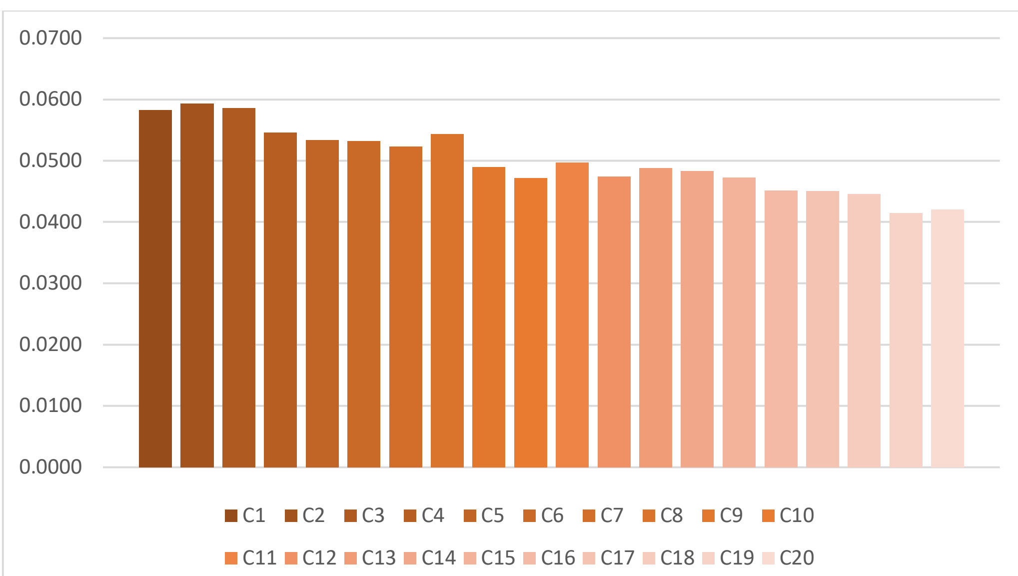

Figure 4:13 Weight ratios for each criterion

4.3.3.2 Prioritization of constraints based on their rank

The weights derived from Fuzzy AHP are used to calculate the net flows and rankings of the constraints using PROMETHEE II (refer to Table 4:18). The rankings indicate each alternative's relative preference or superiority based on the defined constraint. Table-4 displays the ranking of the constraints identified in this case study. Here all the constraints are considered non-beneficial criteria; thus, rank-1 means the least affecting constraint among all, and rank-20 means the most critical or unfavorable criteria. Constraints "Limited exposure to data interpretation methods" (C2), "Susceptibility to cyber threats" (C1), "Limited executive bandwidth amid a competitive market" (C7), "Absence of a regulatory framework" (C3), and "Uncertainty about technology's initial costs and potential benefits" (C6) ranked lower have lower positive net flows or even negative net flows, indicating a higher negative impact on the adoption of big data and AI in the maritime freight industry. Therefore, these constraints are needed to be addressed on priority. This also seems logical because these factors cause other hurdles in implementing big data & AI. It is also pretty clear from the weights of the barriers in table-3 that the above-mentioned barriers (C2, C1, C7, C3, and C6) have higher weightage compared to others which implies that they are more prominent and contribute to a greater extent in the slow execution of big data & AI despite their capability to create a radical advancement in the maritime industry.

Constraint C9 has a weight of 0.0490 and a net flow of 0.3027. However, it does not have the highest weight; its positive net flow indicates the most negligible impact among the identified constraints. However, it is still worth noting and addressing as it contributes to the challenges faced in adopting big data and AI in the maritime freight industry. Constraint C19 and C20 have weights of 0.0414 and 0.04201 with a net flow of 0.2691 and 0.2676. With a positive net flow, these signify a relatively lower negative impact compared to other obstacles. Therefore, these are ranked second and third barriers, indicating their relatively lesser hindrance. The constraints with moderate rank (e.g., C12, C11, C14) have relatively lower positive net flows, implying that they contribute negatively to the overall performance of the adoption. While they may not have the highest impact, their negative impact is significant and can restrict the adoption of big data and AI in the maritime freight industry. Consequently, efforts should be made to address these barriers to facilitate successful implementation.

Table 4:18 Rank of the barriers using PROMETHEE-II

Constraints	leaving flow	entering flow	Net flow	Rank
C1	0.11718	0.55643	-0.43926	19
C2	0.01481	0.55786	-0.54305	20
C3	0.04917	0.21271	-0.16355	17
C4	0.14004	0.19946	-0.05942	15
C5	0.10623	0.16296	-0.05674	14
C6	0.13681	0.20471	-0.06790	16
C7	0.09823	0.41311	-0.31488	18
C8	0.04935	0.03449	0.01487	12
C9	0.30716	0.00449	0.30267	1
C10	0.31671	0.12217	0.19453	4
C11	0.14548	0.03790	0.10758	10
C12	0.27173	0.13942	0.13231	9
C13	0.13009	0.12506	0.00503	13
C14	0.14107	0.07287	0.06820	11
C15	0.18379	0.04842	0.13538	8
C16	0.21396	0.07587	0.13809	7
C17	0.21704	0.06502	0.15202	6
C18	0.21992	0.03243	0.18749	5
C19	0.29830	0.02901	0.26930	2
C20	0.30493	0.03735	0.26758	3

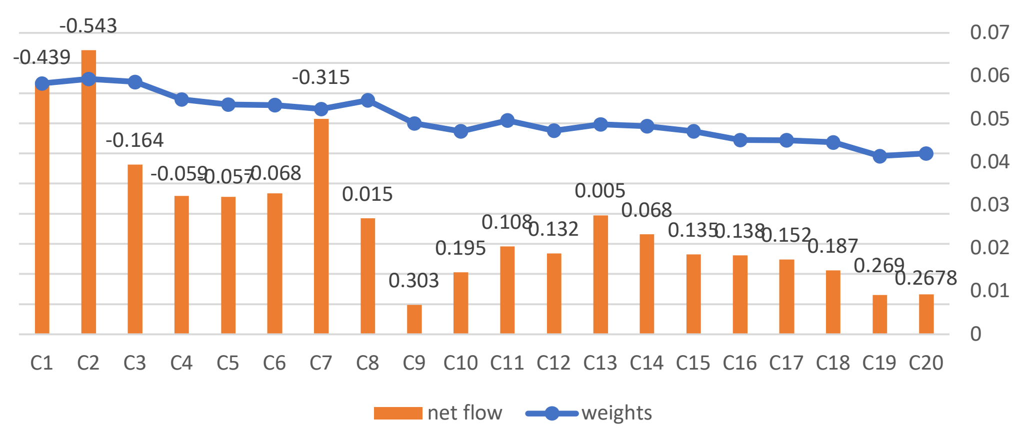

Figure 4:14 Illustration of Weights & Ranks of constraints

4.4 The key Constraints influencing the adoption of IoT in maritime freight

The present work aims to identify the constraints hindering the adoption of the Internet of Things (IoT) in maritime freight. Through a detailed analysis, we seek to pinpoint the most influential barrier impacting IoT adoption and provide valuable managerial insights based on our findings. For this purpose, we employed integrated Fuzzy AHP-Fuzzy TOPSIS approach. AHP a quantitative method, assists individuals or groups in evaluating, analysing, and making decisions about complex, multi-criteria issues. The purpose of this approach is to assess the relationships between different priorities within a given set of choices using evaluation and observation-based rating scales (Piyumi et al., 2021). Notably, the method emphasizes the significance of decision makers' intuitive judgment and consistency when considering factors. AHP enables experts to apply their knowledge and blend it with objective and subjective information in a logical sequence. Moreover, it integrates both aspects of human reasoning, involving both subjective and quantitative elements. The subjective aspect is expressed through a hierarchical arrangement, while the quantitative aspect is conveyed through description and assessment. Preferences are conveyed through figures that can be used to depict the perception of all intangible and tangible issues, capturing an individual's emotions, instincts, and opinions. Whereas, Fuzzy TOPSIS is employed to rank these barriers on the basis of their preference score.

The Mean Strategy using Fuzzy set theory, developed by Professor Zadeh in 1965, is exclusively grounded in addressing uncertainty stemming from imprecision, vagueness, and lack of precision. For instance, expressing subjective attributes like "He is a tall man" cannot be precisely captured using numerical equations or explanations. In Vietnam, the definition of "high" might vary among individuals, exemplifying the challenge of expressing such concepts precisely. Fuzzy set theory has proven effective in addressing problems that lack sharp boundaries and precise numerical values. Fuzzy numbers, distinct from rigid words and mathematical equations, closely resemble human judgements in dealing with such uncertainties. The computational steps of the integrated method are shown in methodology chapter. Figure 4:15 depicts the flowchart of FAHP-FTOPSIS method.

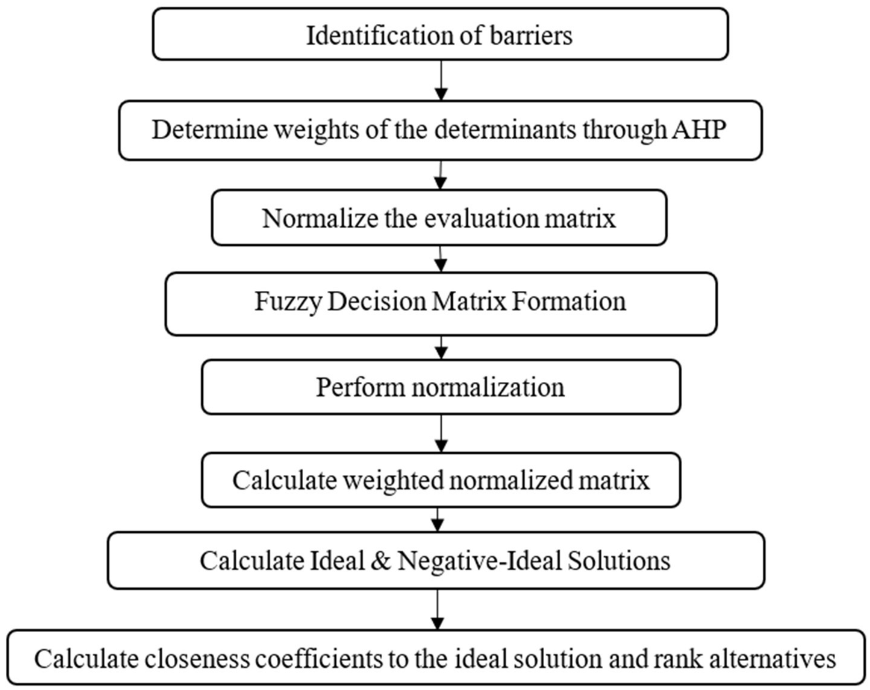

Figure 4:15Flowchart for FAHP-FTOPSIS approach

4.4.1 Data collection

After conducting an extensive literature review and consulting with experts, we identified barriers that impede the implementation of IoT in the maritime freight industry. Initially, we approached 31 experts, of which 20 responded within 4 weeks, resulting in a response rate of 64.52%. Among the respondents, 45% were industry experts, while 55% were academic researchers specializing in supply chain and operations research. Public sector representation accounted for 45.45%, with private institutions representing 36.36%. Within the industry expert group, 22.22% held senior managerial positions across various departments, 22.22% were project managers, 22.22% served as IT managers, and 22.22% were export managers. Additionally, 11.11% were custom service managers. The academic professionals have accumulated over nine years of experience, while industry experts have been actively engaged in their respective fields for seven years. The identified barriers were finalized based on expert input, detailed in Table 4:20. Subsequently, we distributed a questionnaire using the Likert scale (refer to Table 4:19) to gauge the impact of each constraint on IoT implementation in maritime freight. Data collection occurred via email and WhatsApp during the winter of 2022. Finally, Table 4:20 summaries the list of barriers collected through literature review and expert opinion.

Table 4:19 Linguistic scale for the relative Importance

Crisp number	Linguistic terms	Fuzzy Sets
1	Very Low Influence	(1,1,1)
3	Low Influence	(2,3,4)
5	Moderate Influence	(4,5,6)
7	High Influence	(6,7,8)
9	Very High Influence	(9,9,9)

- ***The key constraints to IoT adoption in maritime freight system***

On the basis of a comprehensive review of the relevant literature, and the opinions of industry professionals, a total of 14 constraints (shown in Table 4:20) have been identified. The selection procedure for the factors has been elaborated in the data collection section.

Table 4:20 List of barriers to IoT adoption in maritime freight industry

Sr. No.	Critical Barriers	Description	References
1	Poor Infrastructure	Poor infrastructure often results in limited or unreliable connectivity, affecting the ability of IoT devices to communicate and transmit data effectively.	(Farquharson et al., 2021; Kashav et al., 2021)
2	Fragile towards hacking	The vulnerability of IoT systems to hacking poses a significant risk to the maritime industry.	(Ashraf et al., 2022; Tran-Dang et al., 2020)
3	Data security issue	This barrier points to concerns related to the protection and integrity of data generated and transmitted by IoT devices in maritime freight.	(Aslam et al., 2020; Ding et al., 2021)
4	Vulnerability	This can include vulnerabilities in hardware, software, or communication protocols, raising the risk of system failures or unauthorized access.	(Akpan et al., 2022; Awan & Al Ghamdi, 2019)

5	Lack of understanding	This barrier highlights a gap in knowledge and comprehension among stakeholders regarding IoT technologies in maritime freight.	(Nižetić et al., 2020; Tijan et al., 2021)
6	Shortage of High skilled workers	The shortage of skilled professionals capable of managing and maintaining IoT systems poses a challenge.	(Kuteyi & Winkler, 2022)
7	High Implementation Cost	It includes expenses related to acquiring, integrating, and maintaining IoT systems, potentially straining financial resources.	(Brunila et al., 2021; Jović et al., 2020)
8	Resistance to Change	This can be rooted in organizational culture, fear of job displacement, or reluctance to embrace unfamiliar processes.	(Brunila et al., 2021; Raza et al., 2023)
9	Long Lifecycle of Vessels	The extended lifecycle of maritime vessels poses a challenge to the rapid integration of IoT technologies.	(Ang et al., 2017)
10	Requires continuous upgradation	The need for regular updates and upgrades in IoT systems may present logistical and operational challenges.	(Tan & Sundarakani, 2021; Umair et al., 2021)
11	Regulatory Compliance	Adhering to stringent maritime regulations while implementing IoT technologies can be complex.	(Donepudi, 2014; Kim et al., 2020)
12	Limited Standardization	The absence of standardized protocols and frameworks for IoT devices in maritime freight creates interoperability challenges.	(Ahmed & Rios, 2022; Papadakis & Kopanaki, 2022)
13	Interoperability Issues	Interoperability issues can restrict the ability of different IoT devices to collaborate and share information effectively.	(Brunila et al., 2021; Tran-Dang et al., 2020)
14	Scalability Challenges	Difficulties in scaling IoT solutions across a fleet of vessels or a network of ports may arise due to the diverse nature of maritime operations and logistics.	(Rahman et al., 2022; Zhang et al., 2022; Zhang et al., 2021)

4.4.2 Empirical study

The proposed framework includes two essential steps: allocating weights to each constraint and establishing their ranks. Combining these two components yields the rank of the factors.

The first stage involves assigning weights using fuzzy pairwise comparisons among the criteria. The pairwise comparison matrix is constructed based on expert opinion and solved using the fuzzy AHP technique, as shown in equation 3-15. After that, with the help of the succeeding equations, the geometric means of these values are calculated to obtain a consensus pairwise comparison matrix presented in Table 4:21. Next, crisp weights are calculated using equation 3-19 and depicted in Table 4:21.

The final criteria ranking has been assigned using the Fuzzy TOPSIS method, considering the previously calculated criteria weights obtained through the Fuzzy Analytic Hierarchy Process (AHP). The decision matrix has been normalized using Equation 3-29, and the positive ideal and negative ideal solution for all pairs of criteria have been calculated using Equations 3-35 and 3-36. The distance from positive ideal solution and negative ideal solution for various criteria have been computed using Equations 3-37 and 3-38 and are shown in Table 4:22. The priority score for each criterion and their relative rankings have been determined using equation 3-39 and are presented in Table 4:22.

4.4.3 Results & Discussion

The weighted analysis conducted for the selected barriers in the context of IoT adoption in the maritime freight transport industry provides insights into their relative importance (refer to Table 4:21 & Figure 4:16). The highest relative weight in the analysis is attributed to Barrier B7 with a substantial weight of 0.068, signifying its significant influence on the overall assessment of barriers. Following B7, other noteworthy barriers in descending order of their influence include B5 (weight: 0.0619), B2 (weight: 0.046), B14 (weight: 0.0416), and B3 (weight: 0.0282).

The ranking of the remaining barriers based on their weights follows as; B6 > B11 > B9 > B8 > B10 > B1 > B13 > B12 > B4, reflecting their respective levels of importance in driving the overall ranking of barriers within the resistance assessment framework.

Table 4:21 Weights of barriers computed through Fuzzy AHP

Barriers	Fuzzified Geo. Wt.	Weight
B1	(0.390, 0.474, 0.602)	0.0083
B2	(2.202 2.696, 3.238)	0.046
B3	(1.314, 1.644, 2.019)	0.0282
B4	(0.194, 0.232, 0.293)	0.0041
B5	(2.921, 3.633, 4.370)	0.0619
B6	(1.015 1.265, 1.551)	0.0217
B7	(3.123, 4.006, 4.844)	0.068
B8	(0.581 0.709, 0.882)	0.0123
B9	(0.737, 0.960, 1.271)	0.017
B10	(0.495 0.598, 0.750)	0.0105
B11	(0.906, 1.182, 1.531)	0.0207
B12	(0.237, 0.279, 0.34)	0.0049
B13	(0.361, 0.435, 0.554)	0.0077
B14	(2.084, 2.452, 2.854)	0.0416

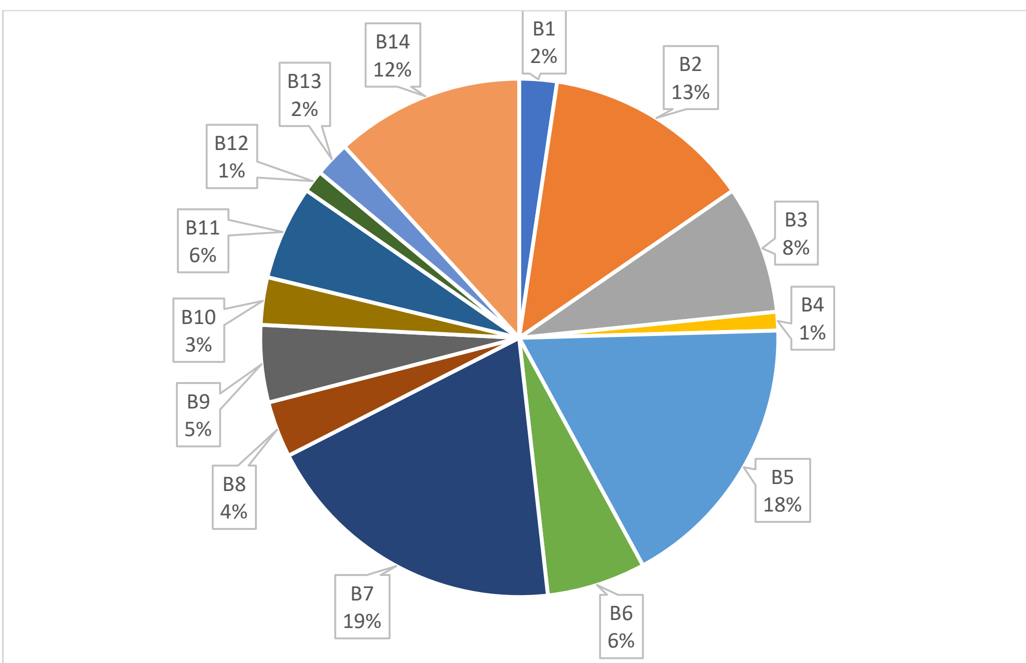

Figure 4:16 The weights of barriers hampering IoT adoption in maritime freight industry

In the following section, an in-depth analysis of the barriers will be undertaken based on their assigned ranks. This detailed examination aims to offer a thorough comprehension of the distinctive traits of each barrier and their potential ramifications on the maritime freight transport industry. The insights gained from this analysis will serve as a foundation for developing strategies to confront and alleviate these barriers, with the overarching goal of bolstering the industry's efficiency and resilience in addressing various challenges.

The priority scores, obtained through Fuzzy TOPSIS, were used to determine the rankings of barriers, as shown in Table 4:22 & Figure 4:17. In this context, the rankings represent the relative preference or severity of each identified barrier to IoT adoption in the maritime industry. 'High Implementation Cost' has the highest priority score, ranking 1st. Its weightage suggests a significant influence on hindering IoT adoption, highlighting the substantial impact of implementation costs. Followed by 'Lack of Understanding' with a priority score of 0.965, is identified as a major obstacle to IoT adoption in the maritime industry. 'Fragile towards Hacking' got ranked 3rd with a priority score of 0.864. Vulnerability to hacking is recognized as a prominent barrier, indicating the industry's susceptibility to cybersecurity threats. Similarly, other remaining barriers, such as 'Regulatory Compliance' highlight challenges as; stringent regulations can act as both a driver and a barrier. While compliance is crucial, navigating complex regulatory landscapes may slow down the adoption process. Data Security Issue is emphasizing concerns related to the protection of data in maritime IoT systems. The 'Long lifecycle of vessels may slow down the integration of IoT technologies, especially on older vessels that may not have been initially designed to accommodate modern IoT systems. These rankings provide insights into the relative impact of each barrier, guiding stakeholders in addressing the most critical challenges first for successful IoT adoption in the maritime sector.

Table 4:22 Priority score and ranking of barriers using Fuzzy TOPSIS

Barriers	Distance(d^+)	Distance (d^-)	($d^+ + d^-$)	Priority Score	Ranking
B1	0.535	0.878	1.413	0.379	12th
B2	1.218	0.192	1.410	0.864	3rd
B3	0.894	0.511	1.405	0.636	5th
B4	0.424	0.982	1.406	0.302	13th
B5	1.377	0.050	1.427	0.965	2nd
B6	0.596	0.809	1.405	0.424	11th
B7	1.370	0.033	1.403	0.976	1st
B8	0.636	0.769	1.405	0.453	10th
B9	0.869	0.537	1.406	0.618	6th
B10	0.654	0.752	1.406	0.465	9th
B11	0.970	0.435	1.405	0.690	4th
B12	0.098	1.306	1.403	0.070	14th
B13	0.676	0.731	1.407	0.480	8th
B14	0.858	0.552	1.410	0.608	7th

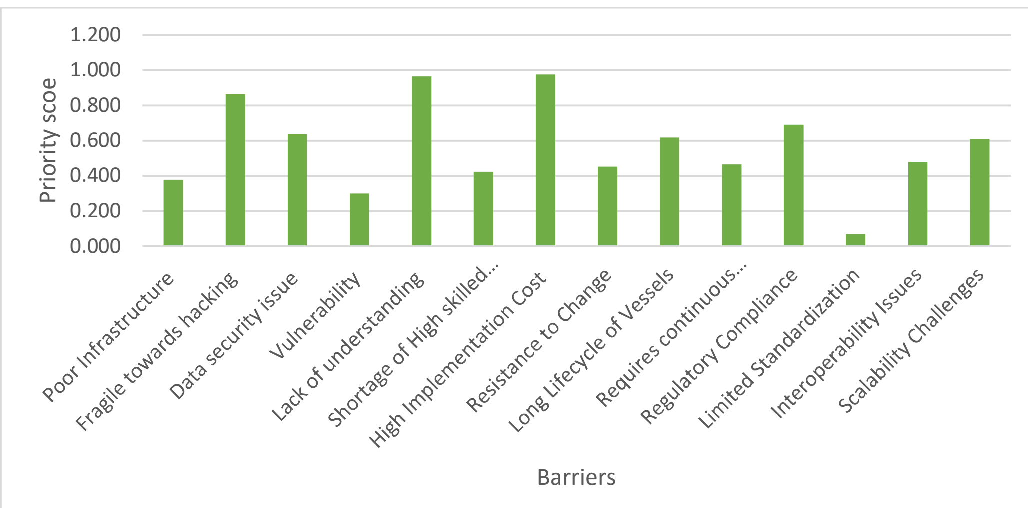

Figure 4:17Pictorial presentation of priority score of barriers

4.4.3.1 Sensitivity Analysis

The sensitivity analysis conducted on the FAHP-FTOPSIS framework revealed insightful findings. Across different scenarios represented by cases 1 through 7, varying weightages were assigned to the experts, with one expert's opinion carrying more weight while others were equally weighted. In one case, all experts were assigned equal weightage. Despite these fluctuations, the overall outcomes of the analysis remained consistent as depicted in Figure 4:18. Notably, the priority scores of the alternatives, crucial for decision-making, remained stable across all scenarios. This suggests that the ranking of alternatives, essential in evaluating different strategies or options, was resilient to changes in experts' weightings. This consistency underscores the robustness and reliability of the FAHP-FTOPSIS framework in decision-making processes, demonstrating its effectiveness in providing consistent and dependable results despite variations in input parameters.

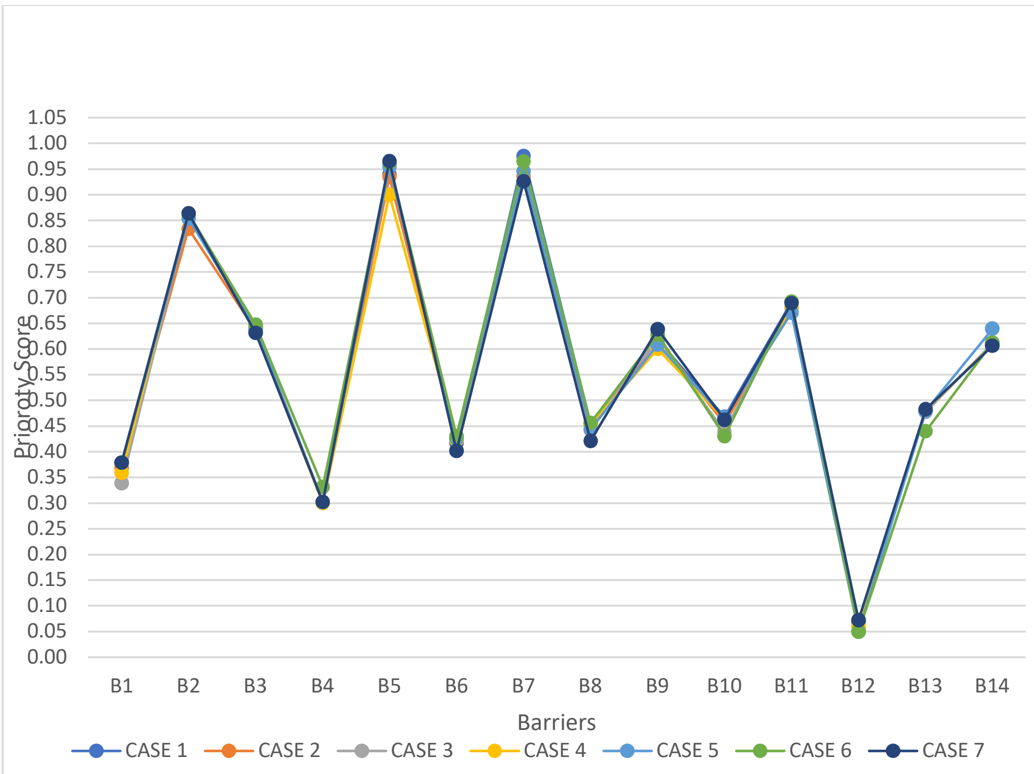

Figure 4:18Sensitivity Analysis Results of FAHP-FTOPSIS Framework

4.5 Concluding Remarks

The maritime and shipping business is gradually and cautiously adopting new and cutting-edge technologies to stand sustainable. The globe as a whole and various industries are being affected by the new trend of digitisation. In an effort to outperform the competition, the maritime industry and its stakeholders are attempting to incorporate those technologies into their business processes and enhance sustainability.

However, it is not as simple as it may appear. Whenever a novel concept is implemented in the real world, it must overcome numerous obstacles. Consequently, the adoption of key digital technologies such as blockchain, big data and AI, and IoT in the maritime freight industry is affected by various factors, and those factors need to be studied comprehensively to tackle them.

Blockchain is one offshoot of upcoming digital innovations such as digital twins, deep learning and big data that have caught the attention of industries around the world. However, its adoption has not yet matured, especially in maritime freight. Therefore, this study identifies the factors influencing blockchain adoption in maritime freight and assesses them with a hybrid SEM-ANN approach. The data was collected from 250 respondents and was used to validate the research model. A number of studies have used SEM and ANN methods in isolation, rather than in combination. The existing study used a combination of SEM-ANN tests hypotheses by uncovering causal relationships. In this study, the output of SEM is integrated as an input for ANN, following the recommendations provided by Hayat et al. (2021).

The results suggest that social, institutional, and organizational factors are of paramount importance. At the same time, factors from social, institutional, and organizational dimensions are also important factors for blockchain adoption within Asian MFT. Although the technological and infrastructural factor is also essential however it contributes comparatively less to BCT adoption as illustrated in the results of SEM analysis.

There are several aspects that include subjective and qualitative judgements in a complex decision-making and evaluation process. When this happens, hybrid decision making approaches may be effectively used to process coefficients, and interrelationships, and to rank the relevance of each. A hierarchical model based on the elements influencing blockchain adoption has been constructed in this research. A coordinated MCDM approach called grey-DEMATEL-ANP (g-DANP) is used to analyse the suggested structure. The computational outcome supports the idea that the suggested model can assist practitioners and policymakers in making better decisions to strengthen maritime freight enterprises, particularly in situations when a number of elements are interrelated. A combination of grey-DEMATEL and ANP was utilised to successfully attain strategic judgements by increasing the computational efficacy of ANP. To prevent abuse and promote interoperability, rules for using blockchain technology should be developed on a worldwide basis. The practical and managerial implications of this study suggest that the findings will have utility for the freight logistics sector, blockchain service providers, and governmental organisations. Specifically, these stakeholders can leverage the identified critical factors highlighted in this study to effectively implement blockchain technology. Furthermore, it is worth noting that managers overseeing maritime freight firms have the opportunity to get valuable insights through the sequenced adoption route regarding the key factors involved in the adoption of blockchain technology. This knowledge may assist them in formulating effective strategies aimed at enhancing their competitive advantage.

Furthermore, the study undertakes a comprehensive analysis of the critical constraints to big data and AI integration in maritime freight system. It proposes a barrier assessment framework for the adoption of big data and artificial intelligence using the FAHP-PROMETHEE II method. First, the criteria system is constructed using 20 critical constraints, and the weighting of the criteria is determined using the FAHP method. Second, the evaluation information for the constraints is gathered using linguistic terms, and the decision matrix is constructed using Fuzzy sets. Last but not least, the FAHP & PROMETHEE II method is then utilised to calculate the weights and ranking results.

The findings of the study draw attention to several significant constraints, including "Limited exposure to data interpretation methods," "Susceptibility to cyber threats," "Limited executive bandwidth amid a competitive market," "Absence of a regulatory framework," and "Uncertainty about technology's initial costs and potential benefits." Each obstacle poses its one-of-a-kind difficulties, which need to be conquered if we remove them and make it possible for the marine industry to implement big data and AI successfully.

Moreover, this study delves into key barriers affecting IoT adoption in the maritime freight industry, highlighting the critical barriers requiring attention from industry stakeholders and managers. The study identifies and prioritizes key barriers through the application of Fuzzy AHP and Fuzzy TOPSIS methodologies. Barriers such as "Lack of Understanding" and "Resistance to Change" emerged as critical challenges requiring attention from industry stakeholders and managers. Furthermore, we examined how each identified barrier impacts the adoption of IoT in the maritime freight industry. The study underscores the significance of these barriers in hindering the seamless integration of IoT technologies into maritime operations. For instance, barriers like "Lack of Understanding" and "Resistance to Change" can impede organizational readiness and internal acceptance of technological innovations. And lastly, the study provides insights into practical implications. It emphasizes the necessity for targeted managerial initiatives to overcome barriers effectively. By focusing on cultivating awareness and fostering a positive attitude toward technological change, managers can bridge knowledge gaps and mitigate internal resistance. Education and change management strategies are highlighted as pivotal for facilitating the adoption of IoT technologies sustainably in maritime operations.