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RESEARCH ARTICLE

A FACTOR ANALYSIS OF SUPPLY CHAIN DISRUPTIONS: EVIDENCE FROM MANUFACTURING COMPANIES

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Abstract

Supply chain vulnerability has become an issue of significance for many companies. This study conducted a factor analysis of supply chain disruptions faced by bottled water manufacturing companies in Ethiopia. Descriptive and explanatory research designs were employed. The data were collected from 347 employees of manufacturing companies using structured questionnaires. Exploratory and confirmatory analyses were employed. The exploratory factor analysis revealed a clear factors structure with supply chain disruption factors. The factor loadings were substantial and in alignment with the theoretical constructs, with minimal cross-loading issues. The reliability analysis showed that each factor had acceptable internal consistency, supporting the validity of the constructs. The confirmatory factor analysis results confirmed a good model fit, supporting the structural validity of the model. The standardised factor loadings were all significant, indicating strong item-construct relationships. The reliability and validity assessments confirmed that each factor was reliable and valid, with evidence for both convergent and discriminant validity. The measurement model, hence, is robust and reflects the underlying constructs effectively. The analyses have also provided evidence of the measurement model's validity and reliability, suggesting the use of the constructs for further analysis such as path analysis.

Introduction:-

The performance of worldwide supply chains expands supply chain networks and enhances organisation exposure to supply chain disruptions(Bode and Wagner, 2015). Supply chain disruptions are unanticipated events that disrupt the normal flow of goods and materials within the supply chain and, as a consequence, expose firms within the supply chain to operational and financial risks(Craighead et al., 2007). They occur when there is an unplanned stoppage in the movement of goods, both finished and work-in-progress, within a supply chain(Revilla and Saenz, 2017). Supply chain disruptions have increased in frequency and intensity and led to more significant consequences (Chopra and Meindl, 2016).

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The vulnerability of supply chain disruptions around the world has become a growing concern over the last few years (Langat and Karanja, 2021). For instance, the appearance of COVID-19 in Wuhan, China, in late 2019 that has so far spread all around the world is a cause of supply chain disruptions worldwide. Supply chain disruptions are any occurrences that have negative consequences for regular supply chain operations and, hence, cause some degree of disorder within the supply chain (Chopra and Meindl, 2016).They are considered the most pressing concerns facing firms competing in today's global market place (Marley et al., 2014).

Others highlight the possibility of a negative occurrence destabilising the supply chain, while others describe a disruption in the supply chain as solely relating to the evaluation of physical flow efficiency. Natural catastrophes (Gunessee et al., 2018) and pandemics (Queiroz et al., 2022) can be categorised as random occurrences, as can accidents like machine breakdown or fire or purposeful disruptions like acts of terrorism or sabotage. Each organisation has a different level of sensitivity to a given risk(Sheffi and Rice, 2005). Disruptions in supply chain frequently result from vulnerabilities in supply chain (Juttner & Maklan, 2011).

Supply chain disruption-orientated firms learn from prior disruptions and maintain an awareness of the environment to allow them to manage future disruptions. Effectively developing and managing resources provides the bridge between understanding the disruption environment and preparation to be successful in the face of disruptions (Ambulkar et al., 2015). Depending on the level of trust in the exchange partner involved, the occurrence of a supply chain disruption leads to different information processing needs and different responses(Bode and Wagner, 2015).

Rupture conditions in a supply chain occur when companies face disruptions due to sudden and unexpected events (Ponomarov and Holcomb, 2009). Disruptions in supply chain frequently result from vulnerabilities in supply chain (Juttner and Maklan, 2011). Previous study identified four fundamental factors that influence the impact of disruption on supply chain execution, such as sourcing strategy, inventory management, production planning, and control(Dolgui et al., 2018). The biggest challenge facing supply chain management today is caused by disruptive events. This impact on logistics has been documented in various studies(Liu et al., 2023; Scholten et al., 2020). Supply chain disruptions significantly impair businesses' capabilities since they interfere with the flow of materials and goods, which is a basic requirement for business operations.

Supply chain faults and disruptions can contribute to both short- and long-term losses in revenue and market share. The biggest impact to the firm following a disruption comes not from the physical damages to facilities but from the market share lost to the rivals. The reason for this is because supply chain interruptions may make it impossible for a company to take advantage of robust market demand because of product shortages, which might result in a loss of market share to rivals (Hendricks and Singhal, 2005). Consequently, companies expected prepare ahead and think about risk-reduction techniques they might employ in the event of interruptions. By employing mitigation strategies, firms or supply chains may bounce back from interruptions fast(Rezapour et al., 2016).

The spread of disruption through a supply chain and its associated impacts are the ripple effects(Jaleta, 2021). Thus, taking proactive action, properly configuring supply chain systems, and developing rapid reaction capabilities to recover from disruptions provide companies an opportunity to improve and obtain sustainable competitive advantage (Pu et al., 2022). Similarly, organisational managers who can respond to supply chain disruptions efficiently and rapidly obtain an additional advantage over their competitors (Varzandeh et al., 2016).

Studies endorse numerous factors to capture susceptibility and supply chain capability. The major factors such as turbulence, deliberate threats, external pressures, resource limits, sensitivity, and connectivity are categorised under vulnerability(Fiksel et al., 2015; Pettit et al., 2010). Turbulence is the most vulnerable type of supply chain disruption, followed by deliberate threats, external pressures, and resource limit disruptions, as ranked by (Pettit et al., 2013). This study focused on turbulence, deliberate threats, external pressures, and resource limits factors. This study, therefore, examined a factor analysis of supply chain disruptions in bottled water manufacturing companies in Ethiopia.

Research Methodology:-

Research design

This study is conducted in Ethiopia, taking bottled water manufacturing companies as a case study. This study adopted descriptive and explanatory research designs. A quantitative research approach was also used (Zikmund et al., 2010). The individuals' demographic traits are described using a descriptive approach. The link between the observable variables and their underlying latent constructs is ascertained through the use of the explanatory research design. The quantitative research approach is employed to present study objectives using empirical assessments that involve numerical measurement and analysis (Walliman, 2011).

Sampling Methods

This study focused on medium- and large-scale bottled water manufacturing companies in Ethiopia. There were 72 bottled water manufacturing companies operating during the study, of which 10 were purposefully selected based on their high production capacity and highly consumable products; see Table 1. This study used the sample size formula (Yamane, 1967), where n is the sample size, N is the total population, and e is the degree of precision, as shown below: $n = \frac{N}{1+N(e)^2}$, $n = \frac{3,125}{1+3,125(0.05)^2} \approx 355$.

Table 1:- Proportionality of the sample size.

S/N	Bottled Water Companies	Population Size	Proportional Sample Size
1	Gold Water	564	(564*355)/3125=64
2	One Water	601	(601*355)/3125=68
3	Top Water	340	(340*352)/3125=39
4	Fham water	259	(259*355)/3125=29
5	Daily Water	234	(234*355)/3125=27
6	Arki Water	196	(196*355)/3125=22
7	Cheers Water	157	(157*355)/3125=18
8	Boss Water	126	(126*355)/3125=14
9	Forest Water	151	(151*355)/3125=17
10	Africa Water	497	(497*355)/3125=57
Total		3125	355

Source: Author computation (2023/24)

Therefore, a sample size 355 employees was determined using simple random sampling technique. From 355 questionnaires distributed to the respondents, 347 (97.75%) were correctly filled out and returned.

Ethical approval

This study was accepted by the Board of Postgraduate Studies and Research in the Faculty of Business Studies of Punjabi University, Patiala, India (2442/Research) on March 29, 2023. Written informed consent was obtained before data were collected from participants. The questionnaires were made anonymous, and participants had the freedom to opt out of the participation at any point if they felt uncomfortable.

Data collection methods

This study employed structured questionnaires (Walliman, 2011) to collect primary data from company employees regarding supply chain disruptions. The items were initially developed in English and subsequently translated into the local language. A 5-point rating system was used to arrange the survey results in an ordinal way, with a score of five denoting strong agreement and a score of one denoting considerable disagreement. These scales are valuable tools in social science and attitude research endeavours(Croasmun and Ostrom, 2011).

Data Analysis Methods:-

This study used both descriptive and inferential statistics. The descriptive statistics for instance percentage and frequency were employed to explain the participants' background information. Inferential statistics such as exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were used to discuss the supply chain disruptions. The analysis was carried out using the Statistical Package for Social Sciences with Analysis of Moment Structures (SPSS-AMOS) software, version 23.

The ultimate goal of EFA was to come up with a pattern matrix where acceptable values of the Kaiser-Meyer-Olkin (KMO) test, Bartlett's test of sphericity, factor loadings, and factor correlation matrix are satisfied. Accordingly, Varimax rotation with Kaisarnormalisation, scree plot, principal component analysis, and an absolute value of the standardised factor loading greater than 0.5 was set to run EFA. KMO and Bartlett's test were examined for each construct to suit sampling adequacy. The result of KMO and Bartlett's test for all constructs were statistically significant (KMO > 0.60, p<0.05, = 0.000). Bartlett's test of sphericity should be significant (p <0.05) for the factor analysis to be considered appropriate. The KMO index ranges from 0 to 1, with 0.60 suggested as the minimum value for a good factor analysis (Tabachnick ans Fidell, 2013).

This study also used CFA to determine if a collection of observed data, based on a predetermined factor structure, reflects many underlying latent constructs. Confirmatory factor analysis (CFA) looks for relationships between hypothesised components and observed variables (Pallant, 2013). CFA enables researchers to test how well the measured variables represent the constructs. CFA enables researchers to examine the fit between the model and the data via the chi-square test, fit indices, and significance tests for factor loadings computed (Hair et al., 2014; Harrington, 2009). The following indices were used for the purpose of reporting (see Table 2).

Table 2:- Indices used for reporting purpose.

Fit Indices	Threshold Values	Sources
χ^2	$\chi 2$, df, p >0.05	(Byrne, 2010; Hair et al., 2014)
χ^2/df	1.0< $\chi 2$ /df	(Hu and Bentler, 1999)
GFI	>0.90	(Joreskog and Sorbom, 1982)
AGFI	>0.90	(Byrne, 2010; Hair et al., 2014)
TLI	>0.90	(Hu and Bentler, 1999)
NFI	>0.90	(Bentler and Bonett, 1980)
CFI	>0.90	(Bentler, 1990)
RMSEA	<0.080	(Browne and Cudeck, 1992)

Reliability and validity of the scale were also tested using Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). The Cronbach's alpha value of greater than 0.70 is an acceptable cut-off point of the reliability test (Mohsen et al., 2011). The composite reliability cut-off value is typically 0.7 or higher. The AVE ≥ 0.5 confirms the convergent validity (Fornell and Larcker, 1981).

Measurement scale

Supply chain disruptions (SCD) consist of 24 items. Each item is being measured using a five-level scale (see Table 3).

Table 3:- Measurement scale of the variables.

Constructs	Items	Sources
Turbulence		(Christopher and Peck, 2004; Hamel and Valikangas, 2003; Pettit et al., 2010)
SCDt1	Our products face unpredictable demand shifts.	
SCDt2	We depend on supplies and/or export markets that experience severe currency or price fluctuations.	
SCDt3	Our imports or exports face recurring disruptions due to geopolitical turmoil.	
SCDt4	Our facilities or markets are frequently exposed to severe natural disasters.	
SCDt5	We regularly face unforeseen technology failures in our operations.	
SCDt6	Our operations are susceptible to a potential health pandemic affecting our employees.	
Deliberate Threats		(Peck, 2005; Pettit et al., 2019; Svensson, 2000)
SCDd7	Our facilities or personnel may be targets of terrorism or sabotage.	
SCDd8	Our products are regularly stolen or vandalized.	
SCDd9	We depend on unionized labour which can be hostile to the firm.	
SCDd10	Our operations are frequently impeded by special interest groups.	
SCDd11	Our products or technologies may be compromised by industrial espionage.	
SCDd12	Our operations or products faced liability claims.	
External Pressures		(Peck, 2005; Pettit et al., 2013; Pettit and Beresford, 2009)
SCDde13	Our products are threatened by frequent competitive innovations.	
SCDde14	Our operations and/or products are subject to changing government regulations.	
SCDde15	Our products faced strong price competition.	
SCDde16	Public opinion exerted significant pressure on our operations.	

SCDde17	Social or cultural changes have had a significant impact on our ability to serve our markets.	
SCDde18	Environmental concerns influenced how we design our products and/or conduct our operations.	
Resource Limits		(Pettit et al., 2010, 2019)
SCDdr19	Our suppliers have limited capacity.	
SCDdr20	Our production capacity is limited.	
SCDdr21	We have limited access to the capacity for distributing products.	
SCDdr22	Raw materials for our products are scarce or in high demand.	
SCDdr23	Utilities are over-extended, and our utility infrastructure is poor.	
SCDdr24	We have difficulty in recruiting and retaining highly skilled workers.	

Results and Discussions:-

The participants demographic background

The study findings indicate that 23.6% and 76.4% were female and male, respectively. This result infers the majority of employees in Ethiopian bottled water manufacturing companies were male. It also shows a significant gender imbalance in the workforce. Most of the participants (74.4%) were bachelor's degree holders, followed by master's degree holders (11.2%) and diploma graduates (10.1%). This finding indicates the majority of the respondents were at least first-degree qualified. These results further indicate that the companies attract educated individuals.

A larger number of the respondents (70%) were from the natural science stream, while 30% of them were from the social science stream. These findings show that the companies recruit more of the workforce with natural science backgrounds. This study's respondents were mostly managerial position holders (55.9%), followed by non-managerial employees (44.1%). These results infer that most of the survey participants were from leadership responsibilities. This study also found that the mean age of the participants was 29.59 with a standard deviation of 6.705, which shows productive-age workforces. The participants' experience was on average 4.77 with a standard deviation of 4.859, which infers employees with moderate professional experience.

EFA of supply chain disruption (SCD)

Table 4 shows that the KMO value for the supply chain disruption scale was 0.766, which is higher than the recommended value of 0.6 (Kaiser, 1974). This means that the correlations are strong enough for factor analysis. Likewise, Bartlett's test of sphericity was statistically significant ($P < 0.05$, = 0.000), confirming the factorability of the correlation matrix (Bartlett, 1954). The researcher checked the assumption of factorability before conducting the factor analysis. Consequently, the researcher reviewed the correlation matrixes and discovered several items with a correlation coefficient of 0.50 and above. Overall, the results demonstrate that the supply chain disruption scale is compatible with the use of EFA.

Table 4:- KMO and Bartlett's test for SCD (23 items).

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.766
Bartlett's Test of Sphericity	Approx. Chi-Square	3584.236
	df	253
	Sig.	0.000

Source: Author computation (2023/24)

Above,

Table 5 indicates factor extraction or total variance explained by supply chain disruption components. The process of factor extraction involves identifying the minimum number of factors that accurately depict the interrelationships among the variables (Shrestha, 2021). There are many approaches to determining the number of underlying factors. However, this study used principal component analysis (PCA) based on the data provided by 347 respondents who completed the supply chain disruption scale.

Table 5:- Total variance explained by SCD components.

Factors	Initial Eigenvalues	Extraction Sums of Squared Loadings	Rotation Sums of Squared Loadings

	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	5.321	23.133	23.133	5.321	23.133	23.133	3.538
2	3.679	15.994	39.127	3.679	15.994	39.127	3.479
3	2.246	9.763	48.890	2.246	9.763	48.890	3.270
4	1.992	8.661	57.551	1.992	8.661	57.551	2.950
5	.910	3.959	61.510				
6	.892	3.877	65.387				
7	.850	3.697	69.084				
8	.831	3.613	72.697				
9	.747	3.248	75.945				
10	.696	3.025	78.970				
11	.601	2.615	81.584				
12	.567	2.465	84.050				
13	.539	2.342	86.392				
14	.484	2.105	88.496				
15	.417	1.815	90.311				
16	.381	1.658	91.969				
17	.372	1.616	93.585				
18	.352	1.529	95.114				
19	.310	1.346	96.460				
20	.254	1.104	97.564				
21	.207	.899	98.463				
22	.188	.817	99.280				
23	.166	.720	100.000				

Source: Author computation (2023/24)

Without the use of rotation and a fixed number of factors, the researcher identified five (5) factors, accounting for 61.030% of the total variance. However, the researcher identified four (4) factors, accounting for 57.551% of the total variance, after applying Varimax rotation and removing one item from SCDR21. Additionally, the researcher computed the communality for the initial extraction, which came out to be 1.00. This suggests that every variable contributes fully (1.00 or 100%) to the solution; the removal of item SCDr21 was due to its cross-loading. This study further employed the scree plot test (Cattell, 1966) to avoid over factoring, as Figure 1 shows below.

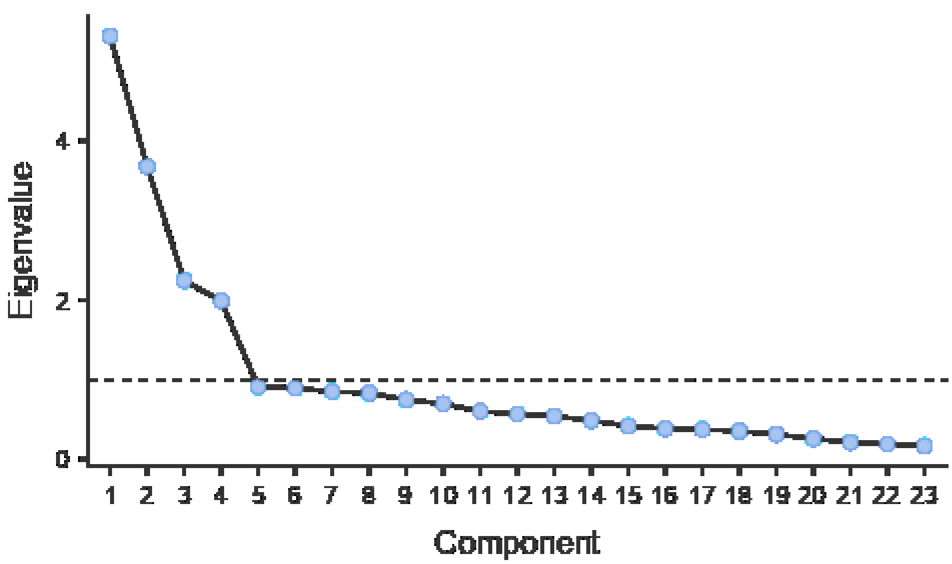

Figure 1:- The scree plot of supply chain disruption scale.
Source: Author computation (2023/24)

Figure 1displays the scree plot of eigenvalues for the initial component solution. The scree plot revealed the turning point at component four (4), exhibiting transition points between components with high and low eigenvalues. Accordingly, this plot verified the prior observation derived from the total variance explained in

Table 5that there were four (4) factors as the best principal components of the solution.

Table 6 displays the final rotation matrix that adequately retains the supply chain disruption factors, with a factor loading ranging from 0.643 to 0.834. Therefore, the researcher loaded item numbers 1, 2, 3, 4, 5, and 6 on factor 1 (turbulence), with a factor loading ranging from 0.644 to 0.83. The researcher loaded item numbers 13, 14, 15, 16, 17, and 18 on Factor 2 (external pressures), with a factor loading ranging from 0.643 to 0.822. Factor 3 (deliberate threats) loaded item numbers 7, 8, 9, 10, 11, and 12 with a factor loading from 0.625 to 0.834. Finally, factor 4 (resource limits) loaded item numbers 19, 20, 22, 23, and 24 with a factor loading from 0.668 to 0.819. However, the researcher removed one item (SCDr21) because of its cross-loading. Therefore, this study considered all the items in the confirmatory factor analysis for further verification, excluding the deleted item from the construct.

Table 6:- Rotated matrix extracted for supply chain disruption scale.

Items	Components			
	Factor 1	Factor 2	Factor 3	Factor 4
SCDt1	.644			
SCDt2	.754			
SCDt3	.678			
SCDt4	.748			
SCDt5	.830			
SCDt6	.768			
SCDd7			.721	
SCDd8			.734	
SCDd9			.665	
SCDd10			.834	
SCDd11			.694	
SCDd12			.625	
SCDe13		.643		
SCDe14		.763		
SCDe15		.696		
SCDe16		.745		
SCDe17		.822		
SCDe18		.768		
SCDr19				.711
SCDr20				.767
SCDr22				.819
SCDr23				.668
SCDr24				.708

Source: Author computation (2023/24)

CFA for supply chain disruption (SCD)

An EFA for the supply chain disruption scale confirmed the presence of four (4) key components. The researcher further verified these components through confirmatory factor analysis (CFA). The fit indices of the initial supply chain disruption scale were made with 23 items (see Table 4.35). In this initial model, all indices, with the exception of X2/df and P-value, performed below the standard model fit criteria, indicating the need for model modification.

Table 7:- Model fit indices summary of CFA for SCD scale.

Fit indices	Original SCD scale (23 items)	Refined SCD Scale (12 items)
X^2	860.921	115.129
df	224	48
X^2/df	3.843	2.399

P	0.000	0.000
GFI	0.834	0.948
AGFI	0.796	0.915
CFI	0.814	0.949
NFI	0.766	0.917
TLI	0.790	0.930
RMSEA	0.091	0.064

Source: Author computation (2023/24)

We removed eleven items (SCDt1, SCDt3, SCDt6, SCDd9, SCDd11, SCDd12, SCDe13, SCDe14, SCDe15, SCDr19, and SCDr24) from the original scale due to their standardized residual covariance exceeding 2.53. As a result, the fit indices of the twelve-item refined supply chain disruption scale got better, and they showed a satisfactory level of model fit (see Table 7above). Further, Figure 1displays the refined confirmatory factor analysis for supply chain disruption. This study used 12 items from the supply chain disruption scale for the structural equation modeling path analysis, which followed the CFA methodology.

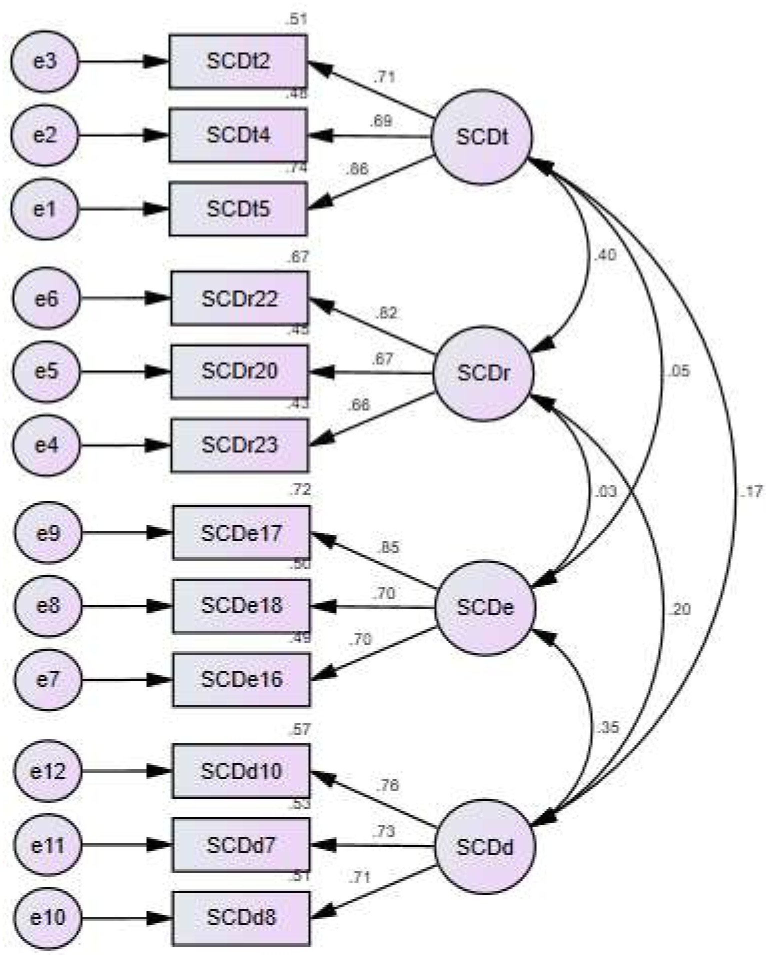

Figure 2:- Model fit indices summary of supply chain disruption scale.
Source: Author computation (2023/24)

This study confirms the internal consistency by calculating Cronbach's alpha to test the accuracy and reliability of the instrument, as shown in Table 8below. The appropriate threshold value for Cronbach's alpha should be greater than 0.7. So, the survey tool was found to be reliable because it had Cronbach's alpha values of 0.796 for turbulence (SCDt), 0.757 for resource limits (SCDr), 0.795 for external pressures (SCDe), and 0.777 for deliberate threats (SCDd).

Table 8:- Reliability for supply chain disruption scale.

Construct	Indicators	Estimate (β)	S.E.	C.R.	P-value	Cronbach's alpha
SCD	SCDt	0.754	.132	8.377	***	0.796
	SCDr	0.717	.119	5.989	***	0.757
	SCDe	0.752	.123	6.666	***	0.795
	SCDd	0.734	.093	6.639	***	0.777

Note: *** $P \leq 0.001$
Source: Author computation (2023/24)

The convergent validity is established when average variance extracted (AVE) is ≥ 0.5. The AVE values corresponding to the component turbulence, resource limits, external pressures, and deliberate threats are 0.574, 0.520, 0.570, and 0.539, respectively; see Table 4.37.

Fornell and Larcker (1981) state that an AVE value of less than 0.5 validates convergent validity, and Table 9 shows that all AVE values exceed this threshold. The composite reliability (CR) values for component turbulence, resource limits, external pressures, and deliberate threats are 0.800, 0.763, 0.798, and 0.778, respectively. It demonstrates the internal consistency of the scale items. This model generally demonstrates good reliability, convergent validity, and discriminant validity.

Table 9:- Validity for supply chain disruption scale.

Factors	CR	AVE	MSV	MaxR(H)	SCDt	SCDr	SCDe	SCDd
SCDt	0.800	0.574	0.163	0.826	0.758			
SCDr	0.763	0.520	0.163	0.785	0.404***	0.721		
SCDe	0.798	0.570	0.120	0.820	0.047	0.025	0.755	
SCDd	0.778	0.539	0.120	0.779	0.168*	0.197**	0.347***	0.734

Note: * $P \leq 0.05$, ** $P < 0.01$, *** $P \leq 0.001$
Source: Author computation (2023/24)

Conclusion:-

Supply chain vulnerability has become an issue of significance for many companies due to today's uncertain and turbulent markets. This study investigated a factor analysis of supply chain disruptions in manufacturing companies. The data were collected from 347 employees of manufacturing companies using structured questionnaires. The data were analysed using EFA and CFA factor analysis. The SCD factors under consideration were turbulence, deliberate threats, external pressure, and resource limits.

EFA revealed a clear factor structure with SCD factors, which accounted for 57.55% of the variance. Factor loadings were substantial and in alignment with the theoretical constructs, with minimal cross-loading issues. The reliability analysis showed that each factor had acceptable internal consistency (Cronbach's alpha > 0.7), supporting the validity of the constructs. The CFA results confirmed a good model fit, with GFI, AGFI, CFI, NFI, and TLI values above 0.90 and an RMSEA below 0.08, supporting the structural validity of the model. Standardised factor loadings were all significant and above 0.5, indicating strong item-construct relationships. Reliability and validity assessments confirmed that each factor was reliable (CR > 0.7) and valid (AVE > 0.5), with evidence for both convergent and discriminant validity.

Therefore, the measurement model is robust and reflects the underlying constructs effectively. The analyses have provided evidence of the measurement model's validity and reliability, supporting the use of the constructs in further analysis such as path analysis.

Implications

This study, theoretically, can allow researchers to understand findings from a factor analysis perspective, providing a comprehensive overview on supply chain disruption of manufacturing companies in developing countries. This research finding can also support addressing knowledge gaps and contribute to a deeper understanding of supply chain disruptions. Moreover, practically, this research can inform policy and managerial decision-making in manufacturing sectors concerning supply chain disruption mitigating strategies in developing states. Hence, policymakers, industry practitioners, and managers can use such evidence-based findings in planning and implementing effective supply chain resilience strategies.

Limitations and future studies

Acknowledging the limitations of this study is essential, while it adds insights to the current body of knowledge, particularly in the field of supply chain disruptions. Firstly, this study was mainly conducted from developing country perspectives. Further studies are advised from a developed country perspective to fully understand the factor analysis of supply chain disruptions. Secondly, this study merely focused on studies published in English. Thus, future investigations can broaden their scope to include subject-matter-related studies published in other languages.Furthermore, the study may have overlooked qualitative information, which could have deepened our understanding of the phenomenon by concentrating primarily on quantitative data. Future research endeavours may benefit from the incorporation of qualitative data to support and amplify the quantitative conclusions.

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