

Development of an Analytics and Collaborations Integrated Supply Chain Risk Management Capability Measurement Instrument based on the Information Processing Theory and the Relational View

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ABSTRACT

Supply chain risk management (SCRM) plays a vital role in any business entity, comprising activities that aim to prevent, detect, respond to, and recover organizations from the impacts of disruptive events. Both analyzing supply chain (SC) data and collaborating with SC partners help firms manage risks effectively during disruptions. Although supply chain analytics (SCA) is an integral element of SCRM, the existing measurement instruments for SCRM do not fully integrate SCA as it is used in the Sri Lankan manufacturing context. However, SC collaborations (SCC) are invariably included in these measurement instruments. Hence, the primary objective of the study was to develop a new measurement instrument for the analytics-and collaboration-integrated SCRM capability of Sri Lankan industrial product manufacturing sector using Organizational Information Processing Theory (OIPT) and the Relational View (RV) as theoretical lens. The study employed an exploratory quantitative research design. The items were generated from both the literature on related measurement instruments and the results of a previously conducted qualitative study. Then, the finalized items were

used in an online survey administered to 205 randomly selected SC managers from industrial product manufacturing organizations in Sri Lanka that engaged in global business. Initially, an exploratory factor analysis was conducted to identify the factors representing the firms' analytics collaboration-based SCRM capabilities. The study proposed a novel four-dimensional measurement instrument for evaluating analytics and collaboration-based SCRM, and it includes: (1) analytics-based risk assessment, (2) information sharing-based risk mitigation, (3) analytics-based risk identification and monitoring, and (4) collaboration-based strategic risk mitigation. Subsequently, a confirmatory factor analysis was conducted to validate the measurement instrument for the identified factors. Given the increasing importance of collaboration and analytics-based SCRM, the validated measurement instrument introduced in this study would be a valuable tool for advancing future research on SCRM.

Keywords: Confirmatory factor analysis, Exploratory factor analysis, Measurement instrument, Supply chain analytics, Supply chain collaboration, Supply chain risk management

1 Introduction

In Sri Lanka, the industrial sector accounted for 30% of Gross Domestic Product (GDP) in 2022 and had the largest number of business establishments (11,006) among manufacturing industries. As a percentage, it is about 78% of the total establishments in the industrial sector (Department of Census and Statistics, 2023). Moreover, industrial product manufacturers contribute to the economy by producing more, thereby driving sustainable long-term economic growth (Ministry of Industries, 2022). Some of these manufacturers are large-scale, with connections to global brands and global SCs (Ministry of Industries, 2022). Apparel, rubber products, electrical and electronic products, automobiles, tiles, and ceramic products are among the products manufactured by such firms (Ministry of Industries, 2022).

However, these manufacturers are exposed to various vulnerabilities, including those of individual organizations, those created by organizational interconnections, and the external environment in which the SC operates due to its global links (Herath et al., 2024; Chen and Fung, 2013). For instance, manufacturers in Sri Lanka are vulnerable not only to various types of climatic changes throughout the year (e.g., rain, floods, droughts, landslides, and cyclones) but also to other adverse events arising from the country's recent socioeconomic and political crises. Nevertheless, these firms are much more vulnerable to global geopolitical events (wars, global economic depressions, terrorist attacks, and global pandemics) because they heavily rely on global SC partners in the raw material imports and finished-goods exports.

However, disruptions in manufacturing SCs are manifestations of risks (e.g., demand, supply, information, external risks) that occur from the original supplier through the delivery of the final product to the end customer (Jüttner

et al., 2003). SC risk refers to any unwanted negative deviation from the expected SC outcome that can adversely affect SC operations and may result in detrimental consequences for the focal firm (Sugathadasa et al., 2020).

Supply chain risk management (SCRM) is vital for continuous smooth operations and it addresses the likelihood and consequences of risks by analyzing sources and implementing appropriate tools, thereby help eliminate, reduce, and control SC risks (Ritchie and Brindley, 2007). Nevertheless, SCRM is an interconnected contemporary approach that comprises the identification, assessment, treatment, and monitoring of SC risks (DuHadway et al., 2017; El Baz and Ruel, 2021; Fan and Stevenson, 2018). According to some scholars, risk identification, risk assessment, risk mitigation and risk control are the four stages of SCRM (Kern et al., 2012; DuHadway et al., 2017; Kleindorfer and Saad, 2005). Risk identification is the discovery of SC risk sources through regular screening of potential risks. In contrast, the risk assessment process involves identifying potential losses, evaluating their likelihood, and assigning significance to them. Risk mitigation seeks to address SC risks with appropriate measures—mitigation strategies before the disruption occurs or contingency plans after the event unfolds (El Baz and Ruel, 2021). Risk control reduces the frequency and impact of SC risks (Saghafian and Van Oyen, 2011).

However, in the information era, some researchers argued for the importance of effectively integrating SC analytics (SCA) with SCRM rather than relying solely on traditional SCRM strategies (Awwad et al., 2018; Ivanov et al., 2019; Ivanov and Dolgui, 2020; Souza, 2014). Shamout (2019) defined SCA as “the extraction, transformation, cleaning, and integration of data generated and captured by SC systems into meaningful patterns for decision makers”. However, SCA can be viewed as a four-layered analytic approach (from outer to inner: descriptive analytics, diagnostic analysis, predictive analytics (goes beyond traditional time series models), and prescriptive analytics (e.g., simulation/ optimization)) that focuses on using information and analytical tools to improve decision-making about material flows within the SC (Awwad et al., 2018; Gunasekaran et al., 2017; Lakpura et al., 2021; Liu, 2022). This was considered the working definition of SCA for this study. Under such a lime-light, Ivanov et al. (2019); Brunekreef and Pournader (2018); Fagundes et al. (2020) introduced several possible scenarios for integrating digital technology, SCA (e.g., Big Data Analytics (BDA), Artificial Intelligence (AI), cloud computing, digital twine, Industry 4.0, Internet of Things (IoT)) with SCRM, particularly these studies focused on integrating BDA at the planning stage to identify supplier risk exposure.

In addition, literature highlighted the integration of SC collaborations (SCC) with SCRM (Belhadi et al., 2021b; Christopher and Lee, 2004; Fan and Stevenson, 2018; Gurtu and Johny, 2021; Saenz and Revilla, 2014). SCC is a long-term partnership in which SC partners pursue common goals, working closely together to achieve mutual advantages greater than those the firms would achieve individually (Cao et al., 2010). For example, Li et al. (2015) noted

that joint SCRM efforts, such as sharing of risk information and risk-sharing mechanisms, can aid in risk identification, forecasting, and early warning.

Moreover, both SCA and collaboration among SC partners assist firms in various ways in managing risks during disruptions. Integration of cognitive analytics (e.g., AI in Google) with experts' judgments to identify risk sources, use of risk scores for risk assessment by getting expert knowledge from SC members (team members, suppliers, customers) are two examples that show how collaborations integrated with SCA are helpful for risk identification and risk assessment.

Organizational Information Processing Theory (OIPT) argues that the greater the task uncertainty, the more information must be processed among decision-makers during task execution to achieve a given level of performance (Galbraith, 1974). Hence, in light of OIPT, it can be argued that the high information requirements, caused by disruptions, can be minimized by effectively integrating SCA with SCRM, which indicates a firms' capability in processing information.

Relational View (RV) suggests that organizations can obtain competitive advantage through relational rents or benefits generated by collaborative relationships (Cao and Zhang, 2011; Dyer and Singh, 1998). Collaborations between SC members are further strengthened by relational competencies such as trust, communication, cooperation, and integration. Drawing on RV, it can be argued that due to the high global connectivity, most members of global SCs can gain collaboration benefits through relational competencies in managing SC risks during disruptions.

However, despite the availability of measurement instruments for SCRM that are based on OIPT (El Baz and Ruel, 2021; Donadoni et al., 2018; Fan et al., 2017; Kern et al., 2012; Wieland and Wallenburg, 2012), SCA underpinning OIPT (Belhadi et al., 2021a; Srinivasan and Swink, 2018; Shamout, 2019; Hallikas et al., 2021), and SCC underpinning the relational view (Donadoni et al., 2018; Stank et al., 2001; Madhavika et al., 2022; Cao et al., 2010), the instruments covering both collaborations and analytics-based aspects of SCRM on both OIPT and RV, a theoretical perspective is lacking in the literature. Although SCA is an integral element of SCRM, the existing measurement instruments for SCRM do not fully integrate SCA, as it is being used in the Sri Lankan context (Kavindi et al., 2021; Malsinghe et al., 2022; Moazzem et al., 2021); SCA is relatively invariably addressed in some of these instruments (Fan et al., 2017; Kern et al., 2012). Further, it was noted that there are only a few attempts to develop measurements to evaluate an organization's ability to manage SC risks (Giannakis and Papadopoulos, 2016).

Hence, addressing the above gap in both the literature and theory, this study develops a measurement instrument for analytics- and collaboration-integrated SCRM capability based on OIPT and RV.

Moreover, the manufacturing industry needs such a measurement instrument to help organizations respond to changing environmental conditions, the adop-

tion of new technologies, collaborations with SC partners, and the management of emerging risks arising from numerous local and global disruptions. The conceptual framework of the SCRM capability, drawn by incorporating the two theories and the extant literature, is shown in Fig. 1.

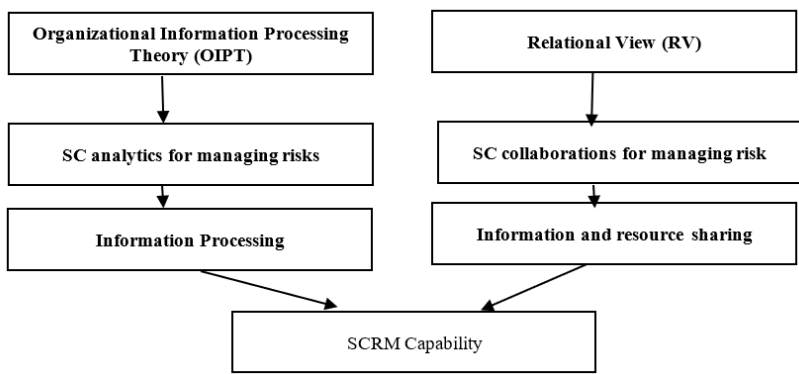


Fig. 1: Conceptual framework of the SCRM capability

2 Methodology

This study employed an exploratory quantitative research approach to develop the new measurement instrument. According to Creswell and Creswell (2018), an exploratory quantitative research design is particularly suitable at the initial stage of measurement instrument development to uncover latent structures and validate predefined models. Exploratory Factor Analysis (EFA) was employed to identify the underlying structure, and Confirmatory Factor Analysis (CFA) was employed to verify construct validity and reliability. For the present study, refinement and validation were treated as the final two stages of measurement instrument development, as suggested in the literature (Ambulkar et al., 2015; Boateng et al., 2018; Hinkin, 1995; Morgado et al., 2017). Both stages with their steps are illustrated in Fig. 2.

2.1 Phase 01: Refinement

Pre-testing can determine whether the items in the proposed measurement instrument are meaningful to the target population (Boateng et al., 2018). Therefore, the questionnaire was initially tested by distributing it online to five purposively selected SC managers in industrial product manufacturing organizations in Sri Lanka. The questionnaire included two questions to gather their comments on the quality and clarity of the questions. All these managers are well-experienced in SC management and have earned postgraduate degrees (MBA/MSc, etc.).

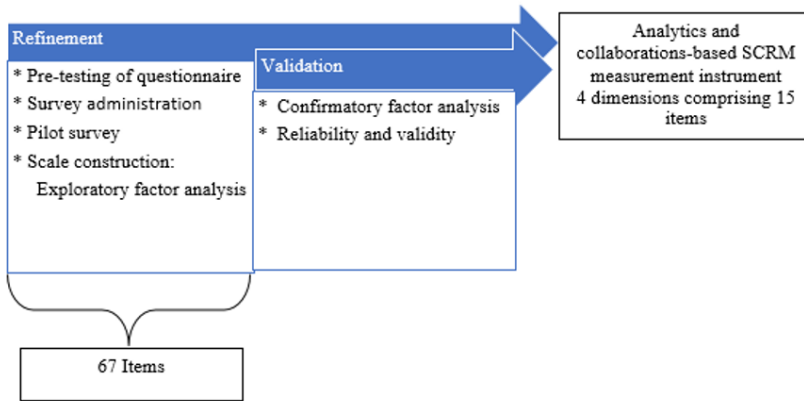


Fig. 2: Steps of the refinement and validation of measurement scales

Population and sample

The population of this study comprises industrial products manufacturing organizations in Sri Lanka that are connected to global SCs. The following criteria were used as the filtration criteria of the population:

1. Each manufacturing organization should belong to either the Ministry of Industries or the Sri Lanka Export Development Board's (EDB) industrial production categorization (Ministry of Industries, 2022; Sri Lanka Export Development Board, 2024).
2. A multinational company with at least one of its manufacturing plants located in Sri Lanka.
3. These organizations should connect with global SCs for imports, exports, or both, and should be within the top 10% exporter categorization group as per the EDB ranking.

After applying the above filtration criteria, the list contained 335 industrial product manufacturing organizations in Sri Lanka that are connected with global SCs and was considered the population of the present study.

The priori-sample size calculator for Structural Equation Modeling (SEM)-based studies introduced by Soper (2020), related to Westland (2010); Cohen (2013) to determine the sample size and took 161 industrial products manufacturing organizations in Sri Lanka that are involved with global SCs. The SC manager of each company was considered the primary respondent of the survey; in the absence of such a position, any relevant officer engaged with SC activities (e.g., production manager, procurement and sourcing manager, operations manager, inventory manager, logistics manager, financial manager, etc.) was eligible to respond to the survey. Scholars often recommend taking a broader sample than the recommended one, which can artificially inflate the measurement instrument's reliability (Tay and Jebb, 2016). Therefore, considering the anticipated nonresponse rate in survey-based studies, the online

questionnaire was distributed to 280 managers. The companies were randomly selected from the identified sampling frame. A total of 205 responses were received, and all were included in the analysis.

Online survey administration

An online survey was designed using Google Forms, as it is a free, convenient, and reliable tool. The online survey link was primarily shared via email. However, at respondents' request, the same link was also shared via WhatsApp with a brief introduction to the survey. In addition, to minimize the non-response rate, a reminder was sent to each respondent two weeks after the initial email was sent.

Before the primary online survey, a pilot survey was conducted with 50 SC managers selected from industrial products manufacturing organizations in the sampling frame; subsequently, the primary survey was conducted.

Response and non-response rate

The survey response rate was 73%, which is considered high, ideally above 60% (Groves and Peytcheva, 2008). A higher response rate always enhances the likelihood that the sample accurately represents the entire population (Groves and Peytcheva, 2008). It had a non-response rate of nearly 27%, which is typical for most online and email surveys (Groves and Peytcheva, 2008).

Measurement instrument construction

Exploratory Factor Analysis (EFA) is a statistical method used to uncover the underlying structure of a relatively large set of variables (Ziegler and Hagemann, 2015). Hence, EFA was primarily used to select indicators for the new measurement instrument in this study, using IBM SPSS 21.

2.2 Phase 02 Measurement instrument validation

Confirmatory Factor Analysis (CFA) was conducted to assess the measurement instrument validity, as it explicitly and directly tests the goodness-of-fit of the factor model. CFA specifies the "measurement models" that describe how measured variables reflect certain latent variables and assesses whether the data fit the model well (Thompson, 2004). IBM SPSS AMOS 21 was used to test the measurement model.

The quality of the measurement model was further checked through composite reliability, convergent validity, and discriminant validity. Reliability is calculated in several ways. The internal consistency of multiple indicators for each construct was assessed through Cronbach's alpha (Hinkin, 1995). Composite reliability (CR) was used to estimate the extent to which a set of indicators contributes to the measurement of the construct (Hair et al., 2011). Reliability generally should be above 0.7. Reliability in the range of 0.6-0.7 is considered acceptable for exploratory studies, but values above 0.95 are not desirable (Bagozzi and Yi, 1988). Convergent validity involves two measures that

are intended to measure the same construct and demonstrate that they are related (Hinkin, 1995). The average variance extracted (AVE) statistic is used to measure the convergent validity. According to Fornell and Larcker (1981), the AVE should exceed 0.5 to establish convergent validity. Discriminant validity ensures that a measurement instrument is not highly correlated with a measure of a different dimension. There is an argument that the Fornell-Larcker criteria do not reliably detect the discriminant validity issues. As a solution, the Heterotrait-Monotrait (HTMT) ratio was introduced. HTMT values show all pairs of constructs in a matrix format, with a threshold of 0.85 for conceptually different constructs (Hair et al., 2011).

3 Results and Discussion

Table 1 presents the study sample profile. According to Table 1, the majority of the industrial product manufacturing organizations in the sample (nearly 51%) produce apparel and textiles.

Table 1: Sample profile of the study

Product Categorization	Freq.	Product Categorization	Freq.
Apparel and textiles	104	Boat and ship building	2
Rubber finish products	43	Building materials	2
Ceramic and porcelain products	9	FMCG	2
Printing, prepress, and packaging materials	6	Glass and glassware	2
Electrical and electronic related products	5	Leather Products	2
Tea	5	Ayurveda and herbal products	1
Chemicals and plastic products	4	Edible Oil Production	1
Light engineering-based products	4	Mineral processed calcium carbonate	1
Coconut-based products	3	Pharmaceutical	1
Engineering products	3	Tobacco	1
Giftware and Toys	3		

Table 2 presents the respondents' demographic information. According to Table 2, the majority of respondents (112) hold a Master's degree. A minority of the sample holds a PhD (1), while 35 of the respondents have other qualifications (e.g., passed O/L/A/L or some diplomas). Moreover, the majority of respondents hold additional qualifications in the fields of SC management or operations management (approximately 62%). This indicates the respondents' knowledge suitability to answer the survey. Furthermore, the majority of the respondents in the sample (43) have 1-5 years of experience in the cur-

Table 2: Distribution of the demographic information of the respondents

Demographic Variable	Category	Frequency
Highest Education Qualification	Bachelor's degree	56
	Master's Degree	112
	PhD	1
	Other	35
Additional Qualifications	Yes	126
	No	78
Tenure	< 1 Year	14
	1-5 Years	43
	5-10 Years	41
	10-15 Years	38
	15-20 Years	31
	20-25 Years	23
	25-30 Years	9
	30-35 Years	4
	35-40 Years	1

rent organization. 41 respondents in the sample belong to the second-highest tenure category (5-10 years).

No missing data were found in the dataset, as all questions in the online survey were compulsory. The data were checked for outliers before conducting an EFA. According to Hair et al. (2009), anything with a standard deviation less than 0.25 is subject to deletion. Hence, the 128th response/case was removed from the dataset because its standard deviation (0.015) is less than 0.25.

Exploratory Factor Analysis (EFA)

Before conducting an EFA, the values in the bivariate correlation matrix for all items analyzed should be checked, as high values ($r > 0.8$) indicate multicollinearity (Tabachnick and Fidell, 2019). Therefore, Pearson correlations of the indicators were tested; most pairs of items had bivariate correlations > 0.30 , and no pairs had bivariate correlations > 0.8 .

Exploratory Factor Analysis (EFA) was conducted to examine the underlying dimensional structure of the measurement items. Principal Component Analysis (PCA) was used as an exploratory data reduction technique to identify patterns among observed variables and assess the preliminary factor structure of the scale (Ziegler and Hagemann, 2015). PCA was selected to explore the dimensionality of the dataset, and the data were approximately normally distributed.

The initial unrotated solution showed a dominant first factor, indicating substantial shared variance among items (but not more than 50% of the total variance explained by the first factor), confirming no evidence of common method bias. Therefore, promax rotation was applied to improve interpretability and allow for correlated factors (Costello and Osborne, 2005). Factor retention was determined using the scree plot, the Minimum Average Partial (MAP)

test, and theoretical interpretability rather than relying solely on the Kaiser criterion.

Next, an eight-factor model was obtained. In this model, factors 7 and 8 each had only two items, and the 5th factor had only three items. Therefore, the eight-factor solution was not accepted, and the five-factor model was attempted. However, in this model, the 5th factor had only three items. Therefore, these were removed, and the five-factor model was rerun.

Since the five-factor model showed no significant issues, as recommended by Latif (2018), the reliability (internal consistency of items) was assessed using Cronbach's Alpha (a reliability threshold of 0.7). However, the reliability of the 5th factor was recorded below the threshold value, which violates the minimum requirement that items belong to a factor (three factors) (Hair et al., 2011). Therefore, the 5th factor was removed, and a four-factor model was developed with the remaining items and the improved model is shown in the following section.

Table 3 shows the KMO and Bartlett's test result of the four-factor final model.

Table 3: KMO and Bartlett's Test of the four-factor final model

Kaiser-Meyer-Olkin Measure of sampling adequacy		0.898
Bartlett's Test of Sphericity	Approx. Chi-Square	1575
	df	105
	Sig	0.000+

The KMO and Bartlett's Test are popular diagnostic measures of sampling adequacy that compare correlation and partial correlation coefficients (Peiris, 2018). According to Table 3, the Kaiser-Meyer-Olkin measurement (0.898) exceeds 0.5, indicating that the data are suitable for conducting EFA. Bartlett's test of Sphericity is also significant ($0.00 < 0.05$), and the correlation matrix is significantly different from the identity matrix.

Communalities show the proportion of a variable's variance that is explained by the common factors. This helps to assess how well the factor model fits the data by quantifying the shared variance among the variables (Tabachnick and Fidell, 2019). Table 4 provides the communalities of the four-factor model.

As per Table 4, the communalities with extractions are in the range of moderate ($0.60 - 0.70$) to high (> 0.8). Moreover, no item is < 0.40 . Therefore, the analysis with the four-factor model was continued.

Table 5 presents the total variance explained. According to Table 5, the four factors accounted for nearly 70% of the variance across 15 items.

Next, the pattern matrix (Table 6) was analyzed, as its coefficients represent a series of standardized regression coefficients that can be expressed as the variable as a function of factor loadings (Costello and Osborne, 2005). The cutoff value used to suppress low correlations is below 0.4.

As per Table 6, almost all the pattern coefficients, are greater than 0.7, except for the two coefficients of *RI_6* and *RM_2*, which indicate moderate factor loadings (> 0.6).

Table 4: Communalities under the PCA extraction method

Indicators	Extraction
<i>RA</i> ₁₀	0.69
<i>RA</i> ₁₅	0.67
<i>RA</i> ₁₇	0.73
<i>RA</i> ₈	0.75
<i>RI</i> ₁₄	0.63
<i>RC</i> ₃	0.78
<i>RI</i> ₆	0.67
<i>RM</i> ₁	0.82
<i>RM</i> ₂	0.66
<i>RM</i> ₉	0.74
<i>RM</i> ₁₃	0.73
<i>RM</i> ₁₅	0.70
<i>RM</i> ₁₆	0.60
<i>RM</i> ₁₄	0.71

Table 5: Total variance explained by the factors

Component	Initial eigen values			Extraction sums square loadings			Rotation sum of squared loadings
	Total	% of variance	Cumulative%	Total	% of variance	Cumulative %	Total
1	6.76	45.03	45.03	6.76	45.03	45.03	5.47
2	1.66	11.04	56.07	1.66	11.04	56.07	4.97
3	1.11	7.40	63.46	1.11	7.40	63.46	3.86
4	0.99	6.62	70.08	0.99	6.62	70.08	3.70
5	0.65	4.34	74.42				
6	0.60	4.02	78.43				
7	0.52	3.45	81.88				
8	0.51	3.36	85.24				
9	0.44	2.94	88.18				
10	0.38	2.56	90.74				
11	0.32	2.10	92.84				
12	0.31	2.04	94.88				
13	0.29	1.90	96.78				
14	0.26	1.74	98.52				
15	0.22	1.48	100.00				

Next, as recommended by Latif (2018), the reliability of the items in each factor was tested by conducting a reliability test for inter-item consistency. The summary output is given in Table 7.

Table 6: Table of pattern matrix

Items	Component			
	1	2	3	4
<i>RA</i> ₁₀	0.81			
<i>RA</i> ₁₅	0.70			
<i>RA</i> ₁₇	0.81			
<i>RA</i> ₈	0.80			
<i>RI</i> ₁₄	0.82			
<i>RC</i> ₃			0.77	
<i>RI</i> ₅			0.90	
<i>RI</i> ₆			0.69	
<i>RM</i> ₁				0.93
<i>RM</i> ₂				0.68
<i>RM</i> ₉				0.76
<i>RM</i> ₁₃		0.71		
<i>RM</i> ₁₅		0.82		
<i>RM</i> ₁₆		0.78		
<i>RM</i> ₁₄		0.78		

According to Table 7, reliability statistics of all four factors are above the threshold for reliability (> 0.70). This indicates the internal consistency of the measurement instrument items. Moreover, the Cronbach's Alpha if item deleted values of all four factors are not greater than the overall reliability of each factor. This indicates that there are no items to delete to improve the measurement instrument's internal consistency further.

Confirmatory Factor Analysis (CFA)

The four-factor measurement model was used to conduct the CFA depicted in Fig. 3.

In order to evaluate the goodness of fit of a specified model to the observed data, indices such as CMIN (Chi-square), standardized root mean square residuals (SRMR), Comparative fit index (CFI), Tucker-Lewis Index (TLI), Parsimony-adjusted Goodness of Fit Index (PGFI), Parsimony-adjusted CFI (PCFI), Goodness-of-fit index (GFI), Standardized RMR (SRMR), and Root mean square of approximation (RMSEA) are used. Recommended threshold values and the obtained values of all fit indices are presented in Table 8.

According to Table 8, almost all fit indices (CMIN/DF, CFI, TLI, PGFI, PNFI, PCFI, GFI, SRMR, and RMSEA) are within the recommended ranges. Higher values indicate a better fit, except RMSEA and SRMR (because the cut-off values for these indices are always less than 0.08). This confirms that the four-factor measurement model fits the data well, with satisfactory levels of absolute/predictive fit, comparative fit, parsimonious fit, and other fit indices.

Table 7: Inter-item reliability of the four-factor model

Factor number	Reliability statistics (Cronbach's Alpha)	Items	Cronbach's alpha if item deleted
1	0.871	RA_10	0.84
		RA_15	0.84
		RA_17	0.84
		RA_8	0.83
2	0.836	RA_13	0.77
		RA_15	0.80
		RA_16	0.82
		RA_14	0.78
3	0.778	RA_3	0.77
		RA_5	0.60
		RA_6	0.72
4	0.784	RA_1	0.62
		RA_2	0.78
		RA_9	0.72

Table 8: Goodness of fit indices of the measurement model

Fit indices	Recommended value	Source	Obtained values as per the output	Decision
Absolute/ predictive fit				
χ^2/df	Ratio of $\chi^2/df \leq 2$ or 3	Schreiber et al. (2006)	176.093/84 = 2.09	Achieved
P	Insignificant ($p > 0.05$)	Bagozzi and Yi (1988)	0.000	
CMIN/df	< 3	Ullman and Bentler (2012) Schumaker et al. (2022)	2.096	Achieved
Comparative fit				
Comparative fit index (CFI)	≥ 0.90	Bentler (1990)	0.939	Achieved
Parsimonious fit				
Tucker- Lewis Index (TLI)	0.90	Bentler (1990)	0.924	Achieved
Parsimony-adjusted GFI (PGFI)	Range of 0.50, with other indices in the range of 0.90, is not unexpected. Close to 1, better, typically lower than other indexes, and sensitive to model size	Mulaik et al. (1989) Schreiber et al. (2006)	0.631	Achieved
Parsimony-adjusted NFI (PNFI)	≥ 0.50 Very sensitive to model size	Schreiber et al. (2006), Byrne (2013)	0.713	Achieved
Parsimony-adjusted CFI (PCFI)	≥ 0.50 Sensitive to model size	Schreiber et al. (2006)	0.751	Achieved
Other				
Goodness-of-fit index (GFI)	≥ 0.90	Hair et al. (2011)	0.901	Achieved
Standardized RMR (SRMR)	≤ 0.08	Schreiber et al. (2006), Hu and Bentler (1998)	0.06	Achieved
Root mean square residual (RMSEA)	≤ 0.06 to < 0.08 < 0.05 ; close fit > 0.05 to < 0.08 ; fairly fit > 0.8 to 1.0 ; poorly fit	Schreiber et al. (2006), Hu and Bentler (1998)	0.073	Fairly fit

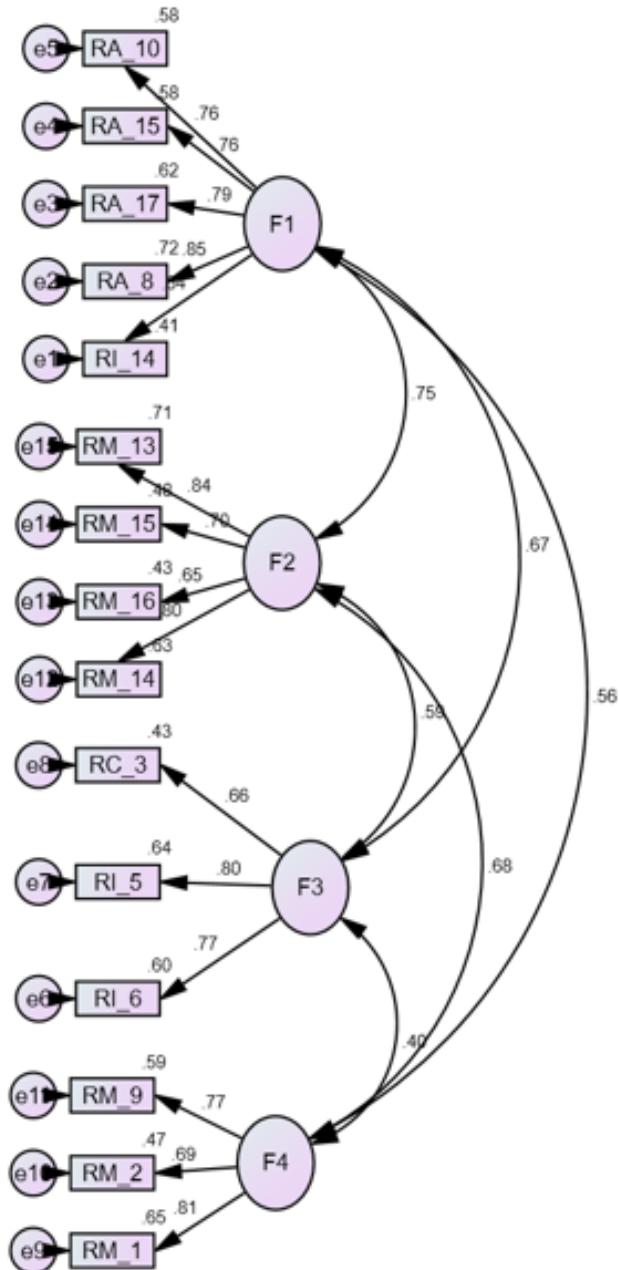


Fig. 3: The four-factor measurement model used for CFA

Reliability and validity analysis

Table 9 presents a summary of the reliability and validity of the measurement instrument items.

Table 9: Internal consistency, reliability, convergent, and discriminant validity of the measurement instrument items

Latent variables	Indicators	Convergent validity			Internal consistency reliability		Discriminant validity
		Factor loadings	Indicator reliability	AVE	Cronbach's alpha	Composite reliability	HTMT
		> 0.6	> 0.5	> 0.5	> 0.60 – 0.90	> 0.6 – 0.9	Significantly lower than 0.85
F1	RI_14	0.644	0.415	0.585	0.871	0.875	Yes
	RA_8	0.851	0.724				
	RA_17	0.787	0.619				
	RA_15	0.763	0.582				
	RA_10	0.765	0.585				
F2	RM_14	0.796	0.634	0.565	0.836	0.837	Yes
	RM_16	0.696	0.484				
	RM_15	0.696	0.484				
	RM_13	0.844	0.712				
F3	RI_6	0.773	0.598	0.557	0.778	0.790	Yes
	RI_5	0.800	0.640				
	RC_3	0.659	0.434				
F4	RM_1	0.809	0.654	0.571	0.784	0.799	Yes
	RM_2	0.686	0.471				
	RM_9	0.766	0.587				

According to Table 9, the internal consistency reliability for the four factors is satisfactory (> 0.70) (Hair et al., 2011). Furthermore, the CR values range from 0.790 to 0.875, indicating that the study's measurements are reliable (Bagozzi and Yi, 1988). In addition, as shown in the same table, all factor loadings exceed the 0.6 threshold (Chin et al., 1997). This ensures the construct reliability is established for each construct in the study.

Table 10 presents the HTMT ratio for Discriminant Validity.

Table 10: Discriminant validity: HTMT ratio

	F1	F2	F3	F4
F1				
F2	0.752			
F3	0.670	0.587		
F4	0.563	0.683	0.399	

As per Table 10, all the HTMT values are below the threshold, which confirms the Discriminant validity of each construct (Hair et al., 2011).

Factor labelling and description of the novel measurement

The four-factor model measurement instrument, explored through EFA and validated through CFA, is given below in Table 11. Further, meaningful and descriptive factor names/labels were assigned to the four factors after thoroughly reading the individual items/indicators loaded under each factor. Denzin and Lincoln (2017) also noted that naming factors in EFA is a subjective, theoretical inductive process. To describe the factors in addition to inductive descriptions, definitions from extant literature were incorporated. Further, each factor and item is assigned an identification code.

Table 11: Four-factor analytics and collaboration integrated SCRM measurement instrument explored through EFA and validated through CFA

Construct	Factor and proposed name	Description of factors	Items	Source
Analytics and collaboration integrated SCRM “Identification, assessment, mitigation, and monitoring of SC risk with the aid of internal information tools, along with SC analytics, information, and strategies of external coordination and collaboration with SC members”	Factor 01: Analytics-based risk assessment (ARA)	“Use of analytical tools to evaluate SC risks, by estimating its impact, provides in-depth information about risks, antecedents, and key vulnerabilities with great emphasis on the interrelatedness of risks trigger events.”	<i>ARA_1</i> : Our organization has a dedicated team to periodically (weekly/monthly, etc.) review SC risks, and this team uses data and analytics to assess SC risks	A mix of literature [Fan et al. (2017)], and primary qualitative data
			<i>ARA_2</i> : Our Company continuously assesses the potential risk in our SC	A mix of literature [El Baz and Ruel (2021), Kern et al. (2012)], and primary qualitative data
			<i>ARA_3</i> : In the course of our risk analysis for all SC partners, we define early warning indicators	
			<i>ARA_4</i> : We classify and prioritize risks using suitable strategies (e.g., material-based risk score, based on three consecutive major issues, etc.)	
			<i>ARA_5</i> : In the course of our risk analysis for individual suppliers or supplier groups, we analyze the possible impact of supply risks	
	Factor 02: Information sharing-based risk mitigation (IRM)	“Connectivity of SC partners that enables them to work effectively to seek and address SC risks by collectively sharing SC risk-related information with appropriate measures through mitigation strategies.”	<i>IRM_1</i> : Our organization has elaborated business continuity plans for certain identified risks	A mix of literature [Chopra and Sodhi (2004), Tang (2006), Wagner and Neshat (2012)] and primary qualitative data
			<i>IRM_2</i> : In my organization, feedback received from the meet-ups with the customers and the information taken from the operational reviews help in mitigating the SC risk	A mix of literature [Madhavika et al. (2022)] and primary qualitative data
			<i>IRM_3</i> : In my organization, suppliers willing to share information such as visibility of their orders, other vendors, possible risks, etc., help to mitigate SC risks	
			<i>IRM_4</i> : In my organization, we are willing to share global supplier-related information, customer requirements, and technology knowledge with suppliers to reduce the quality-related risks	
	Factor 03 Analytics-based risk identification and monitoring (ARIM)	“Use of information and analytical tools to discover the sources of SC risks through regular screening and monitoring of potential SC risks”	<i>ARIM_1</i> : Our organization uses technology-integrated SC analytical tools (e.g., Excel-based score cards, POWER BI-based KPI tracking systems, POWER BI dashboards, and web portals) to identify SC risk	Primary qualitative data
			<i>ARIM_2</i> : Our organization identifies customer risks using data mining and customer trend analysis through software such as Excel and HANA	
			<i>ARIM_3</i> : In our organization, we use digitalized dashboards for visualizing and monitoring SC's KPIs	
	Factor 04: Collaboration-based strategic risk mitigation (CSRM)	“Connectivity of SC partners that enables them to work effectively to seek and address SC risks with appropriate measures through strategic risk mitigation before the disruption occurs or after the	<i>CSRM_1</i> : We prevent operational risk using different strategies (e.g., going for alternative suppliers, keeping buffer stocks for raw materials and finished goods, regional sourcing, having multiple shipping lines and ports, and keeping vendor management inventory	A mix of literature [Donadoni et al. (2018)], and primary qualitative data
			<i>CSRM_2</i> : Our organization follows different strategies (e.g., sharing price pressure risk, regionalizing verticality in the region, transmitting the risk by keeping suppliers' risk, etc.) to share SC risk with partners	A mix of literature [Li et al. (2015)] and primary qualitative data
			<i>CSRM_3</i> : Our organization employs various strategies to mitigate SC risks (e.g., utilizing maintaining alternative suppliers, collaborating with the government to obtain licenses, and increasing safety stock levels).	A mix of literature [Donadoni et al. (2018)], and primary qualitative data

The new multi-dimensional measurement instrument for analytics and collaboration, integrated SCRM capability introduced through this study, consists of four dimensions: analytics-based risk assessment, information sharing-based risk mitigation, analytics based risk identification and monitoring, and collaboration based strategic risk mitigation. It is worth analyzing and comparing it with existing measurement instruments.

Though the multidimensional measurement instrument of SCRM, developed by Chowdhury and Quaddus (2017); Wieland and Wallenburg (2013), consist of four main dimensions: risk identification, risk assessment, risk mitigation, and risk control, the new measurement instrument introduced in this study does not have the dimension of risk control, but it includes other SCRM dimensions (risk identification, risk assessment, and risk mitigation) as introduced by Tang (2006); Kleindorfer and Saad (2005); Wagner and Bode (2009). However, as per Manuj and Mentzer (2008), risk monitoring is a part of risk control, where the risk monitoring helps the organization to be prepared for anticipated risks. Similarly, in the present study, risk monitoring is recognized as a separate dimension together with risk identification.

The dimension names introduced by the present study for SCRM (risk identification and monitoring, risk assessment) are similar to some of the items and dimension names introduced by Kern et al. (2012) for their SCRM measurement instrument. However, it is notable that there was no attempt to particularly look at the usage of collaboration and analytics-based SCRM in the measurement instrument introduced by Kern et al. (2012). Furthermore, as introduced in this study, there is a dimension called “information-sharing-based risk mitigation strategies,” which includes risk mitigation strategies derived from the information sharing of SC members. Similarly, Madhavika et al. (2022) introduced a dimension, “information sharing,” for their SC collaboration measurement instrument. Furthermore, Christopher and Peck (2004) highlighted visibility as an important antecedent of risk reduction, as it enables organizations to track products and proactively identify potential disruptions. Distinctively, the present study introduced two novel dimensions related to two distinct risk-mitigation approaches: information-sharing-based risk mitigation and collaboration-based strategic risk mitigation, which were not present in extant measurement instruments. Hence, the four-dimensional SCRM measurement instrument introduced in this study is novel and bridges a gap in the literature by providing a framework for analytics- and collaboration-integrated SCRM. By introducing a validated multidimensional measurement instrument for analytics- and collaboration-based SCRM, this study bridges a gap in the SCRM literature.

Secondly, the present study findings bridged the theoretical gap by introducing a multi-dimensional measurement instrument for analytics and collaboration, integrated SCRM capability underpinning both OIPT and RV. The two dimensions, namely Analytics-based risk monitoring and Analytics-based risk assessment, are related to the OIPT and could be used to evaluate how organization can enhance SCRM capability if they try to enhance the information

processing capability during disruptions by properly integrating SCA. The other two dimensions, namely information sharing- based risk mitigation and collaboration-based risk mitigation, are related to the RV and could be used to evaluate how organization can enhance SCRM capability if they try to enhance the information and resource sharing capability during disruptions by properly integrating SCC.

Thirdly, the higher management of industrial product manufacturing organizations in Sri Lanka can use this measurement instrument to evaluate their organizations' levels of analytics-based risk assessment, information-sharing-based risk mitigation, analytics-based risk identification and monitoring, and collaboration-based strategic risk mitigation during disruptions. Accordingly, they can proactively manage available resources (SCA, SCC) to support future risk management.

4 Conclusion

The primary purpose of this study was to develop a measurement instrument for analytics- and collaboration-based SCRM, grounded in OIPT and RV. Hence, for item generation, both the literature on the related measurement instruments and the results of a previously conducted qualitative study were used. EFA was mainly used to identify suitable indicators for the measurement instrument introduced in this study. Then, CFA was used to confirm the reliability and validity of the new measurement instrument. The instrument consists of a novel multidimensional measurement for analytics and collaboration-based SCRM that comprises four dimensions: (1) analytics-based risk assessment, (2) information sharing-based risk mitigation, (3) analytics-based risk identification and monitoring, and (4) collaboration-based strategic risk mitigation. The novel SCRM measurement instrument not only bridged the literature and theoretical gap but also opened an avenue for future researchers to conduct more quantitative research in analytics and collaboration-based SCRM, making this a notable academic contribution of the study.

Limitations and future research directions

This study is limited to validating the measurement instrument for SCRM in industrial product manufacturers in Sri Lanka. The generalizability across the manufacturing context in advanced economies that use SCA as it is being understood in an industry 4.0 context [e.g., big data, machine learning, IoT(Internet of Things)] is low. Hence, future researchers would need further validation of factors by extending the study to other industries and different geographical locations. Due to practical limitations in collecting large-sample data in this study, we conducted both EFA and CFA using the same sample. Hence, this has been accepted as a limitation of the study, and future studies are encouraged to re-examine the factor structure using a new, independent sample (with the organizations with restrictive applications of SCA in the Sri

Lankan context) to establish the robustness and generalizability of the findings. Further, future work can be carried out to check the applicability of the findings to the service sector that uses SCA. Moreover, future researchers can use the newly developed measurement instrument for their studies to test hypotheses addressing the impact of SCRM as another major research avenue.

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