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Analysis of vulnerability and capability for development of supply chain resilience framework

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ABSTRACT

The current COVID-19 pandemic has significantly impacted all sectors, including the automotive industry. The automotive industry is one of the industries that contribute significantly to economic growth in Indonesia. With supply chain disruptions and vulnerabilities amid the COVID-19 pandemic, the demand for supply chain resilience is echoing in the business world. It is essential to develop resilience capabilities promptly because supply chain vulnerabilities can cause severe financial loss for organizations. This research aims to group the variables of vulnerability and capability to perform processing more easily in prioritizing the appropriate vulnerabilities and capabilities. The factor analysis method is designed to group variables in many factors with almost the exact nature and characteristics, making it easier to simplify and analyze further. The results of the study found that the vulnerability variable has three factors, namely (i) financial vulnerability, (ii) operational vulnerability, and (iii) external vulnerability, then these three factors are divided into thirteen indicators. While the factors that are formed from the ability variable are five factors, namely (i) cooperation, (ii) anticipation, (iii) financial strength, (iv) capacity, and (v) flexibility, then the five factors are divided into thirteen indicators. Following the research objectives, grouping and simplifying these priority factors can become a reference for researchers or companies to manage supply chains that are more resilient amid disruptions due to the impact of the COVID-19 pandemic effectively and efficiently.

1. Introduction

The world is currently facing a global crisis due to the COVID-19 pandemic. The impact of COVID-19 pandemic has greatly affected all fields, including social and economic. The impact of COVID-19 pandemic greatly affected Indonesia's economic growth in 2020, which fell by 2.9%. One industry that significantly contributes to economic growth in Indonesia is the car manufacturing industry. However, amid the COVID-19 pandemic, the general decline in car sales could erode the car manufacturing industry's Gross Domestic Product (GDP) by 14.10% or equivalent to Rp23.7 trillion. The Association of Indonesian Automotive Industries (Gaikindo) noted that wholesale car sales in 2020 reached 532,027 units, a decrease of 48.4% compared to 2019 [1]. The drastic decline in the number of car sales, in general, will greatly impact the operational activities of car production, especially the impact on the automotive industry supply chain.

The supply chain is an integrated activity starting from planning, coordinating and controlling all processes and activities in industrial activities that aim to meet consumer needs at an efficient cost [2]. Disturbances in one link in the supply chain can disrupt other links [3]. For example, supply disruptions, operational disruptions in warehouses, demanding uncertainty, transportation difficulties, or closure of port and airport facilities are some of the disruptions experienced during the COVID-19 pandemic [4]–[12]. Managing risk has become an important challenge for supply chain managers due to several factors, such as increasing global competition, cost pressures, customer satisfaction, and complexity [13].

The supply chain of the automotive industry during the COVID-19 pandemic will greatly change the way of doing business. Some new trends will require more and more resilience between many stakeholders in an open and dynamic network. It should be possible to achieve thanks to new data collection and adaptability. Considering these dynamic changes and moving logistics, it is necessary to define and categorize, more specifically, the main vulnerability events that affect the supply chain. Some data is collected in the field and should help to make relevant decisions in the event of a breakdown. In order to automatically understand what this data means; it is necessary to detect and classify vulnerability events to find the capability to deal with vulnerabilities.

The factor analysis method is designed to group many variables into several factors with almost the same properties and characteristics, making it easier to process [14]. In exploratory factor analysis, each initial variable can have a factor loading value on several factors. After the value is obtained, a decision will be made on which variable to include in which factor [15]. For example, Lu *et al.* [16] used exploratory factor analysis to identify crucial sustainability assessment criteria in the context of the international port sector. As a result, four sustainability assessment dimensions were identified: environmental material, an economic issue, environmental practices and social concerns. Also, 31 important sustainable assessment criteria were adapted from previous environmental, economic and social studies. In addition, Mor *et al.* [17] explores the factors affecting the supply chain performance of the dairy industry and develop a framework using exploratory factor analysis. The results of EFA

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grouped the 50 statements into eleven factors. The results reveal that the dairy industry needs substantial development in supply chain practice to be competitive and proficient.

Referring to related studies, the use of factor analysis is also relevant to classify supply chain vulnerability and supply chain capability during the COVID-19 pandemic. By grouping the variables of supply chain vulnerability and capability, data processing will be easier to prioritize disturbances and appropriate supply chain resilience.

2. Literature review

2.1. Supply chain resilience

Resilience comes from the Latin word resilience, which means "rising back or bouncing" can be expressed as the ability of a substance or object to return to its original form. The concept of resilience is derived from the developmental theory of social psychology. It is directly related to important issues such as ecological and social vulnerability, politics and psychology of disaster recovery, and risk management under increasing threats [18]. One of the earliest conceptualizations of resilience was expressed as the degree, manner, and speed of restoration of initial structure and function in an ecosystem after a disturbance [19]. The concept of resilience over the years has gradually developed and spread to various domains, with the supply chain being one of the newest members to adapt the concept. The concept of supply chain resilience combines the previous principle with the study of supply chain vulnerability, defined by [20] as an unexpected deviation from the norm and its negative consequences. Therefore, it can be concluded that supply chain resilience is the ability to overcome the unavoidable consequences of risk events to return to the original operation or move to a new, more desirable state after being disrupted [21].

2.2. Supply chain vulnerability

Vulnerability term has been used and defined by various researchers in the field of risk and supply chain resilience. However, there still needs to be a clear agreement in the literature about vulnerability. The main difference between them is that vulnerability highlights the idea of vulnerability to tampering by defining the characteristics of a system or supply chain that will change the likelihood of harm [22]. On the other hand, risk focuses on the likelihood and severity of the consequences of the disorder. It was highlighted in a study [23] in which they argued that, unlike risk analysis, vulnerability analysis focuses on the entire period of the disturbance, including actions to mitigate, remediate, and restart activities after the disturbance occurs to new situations that arise. Stable is obtained. In determining the vulnerability indicators for this study, the vulnerability indicators are grouped into four main factors as described below [24]: (i) strategy vulnerability-mitigation efforts by improving supply chain management to achieve higher values, (ii) operational vulnerability-vulnerability arising from supply chain networks that the organization has little or no control over, (iii) external vulnerability-frequent changes to external factors that are beyond the control of the organization and its supply chain, (iv) financial vulnerability-impact negative finance caused by markets and economies that are beyond the control of the organization and the supply chain. Table 1 shows the relevant research in supply chain vulnerability.

2.3. Supply chain capability

The supply chain must be able to withstand disruptions [21]. Resilience is the supply chain's ability to prepare for unexpected events, respond to disruptions, and recover them by maintaining continuity of operations at the desired level of interconnectedness [18]. According to [25], the capability is an attribute that enables a company to anticipate and reduce disruption. They can prevent actual disruptions and reduce the effects of disruptions or enable adaptation after disruptions, such as developing new products or services or entering new markets. Through the proposed supply chain resilience assessment (SCRAM) assessment and management tool, [25] investigated 14 main capability factors: (i) flexibility in procurement, (ii) flexibility in order fulfillment, (iii) capacity, (iv) efficiency, (v) adaptability, (vi) visibility, (vii) anticipation, (viii) recovery, (ix) deployment, (x) collaboration, (xi) market positioning, (xii) organization, (xiii) security, and (xiv) financial strength. It should be noted here that despite the importance of this capability, previous researchers [24] argue that increase resilience to one threat can increase vulnerability to other threats. For example, increased collaboration among supply chain partners can pose additional threats due to sharing sensitive information.

On the other hand, increased flexibility through sub-contracting can increase supply chain vulnerability to adverse weather conditions in various geographic areas [31]. Therefore, the fact that supply chain resilience strategies are interrelated shows that it is important to understand the trade-offs between appropriate capabilities to mitigate certain critical vulnerability areas. Furthermore, the effect of vulnerability and capability on an organization's supply chain resilience can lead to supply chain disruption. However, this needs to be more researched and should be addressed by previous researchers [32]. Therefore, this study needs to consider the dynamic effect between supply chain vulnerability and supply chain capability among supply chain partners to reduce collective disruptive events in the automobile manufacturing industry. Table 2 shows the previous research in supply chain capabilities.

Table 1.
Related research about supply chain vulnerabilities

Dimension	Indicator	Reference
Strategy Vulnerability	Supplier trust, loyalty, relations, realibility	[25];[26];[27];[21] [28]
	Unpredictability of demand	[25];[26]; [27]; [20];[21]. [28]
	Customer disruptions	[25]; [26]; [27]; [20]; [21];[29]; [30]
Operational Vulnerability	Import/Export channels	[25]; [28]
	Supplier capacity	[25]; [26]; [30] [28]
	Production capacity	[25]; [27]; ;[29] [28]
	Limited manpower	[24] [28]
	Transportation disruption	[27];[30] [28]
	Product quality problem	[27];[29] [28]
External Vulnerability	Global economic shocks	[24]; [28]
	Geoplitical risks	[24]; [28]
Financial Vulnerability	Economic recession	[25]; [26]; [27]; [29]
	Price pressure (competition)	[25]; [26]

Table 2.
Related research about supply chain capabilities

Dimension	Indicator	Reference
Flexibility	Commonality (facilities, processes)	[25];[26];[18]
	Product commonality (modularity, interchangeability)	[27]; [25]; [26]; [18]
Capacity	Reserve capacity (materials, assets, labor, inventory)	[18];[26];[21]
Efficiency	Waste elimination	[27]; [25];[26];[18]
	Labor productivity	[27]; [25]
	Asset utilization	[25]
Visibility	Products, Assets, People visibility	[25]; [21]; [18]
Adaptability	Process improvement, Lead time reduction	[27]; [25]; [26];[21]; [18]
	Learning from experience, Reengineering	[27]; [25]; [26];[21]
Anticipation	Forecasting	[27]; [25]; [26];[21]; [29]
	Contingency planning, preparedness	[25]; [26]
	Risk management, Business continuity planning	[25]; [26]; [21]; [29];[18]
Recovery	Communication strategy	[25]
Dispersion	Distributed decision-making	[25]; [26]
Collaboration	Collaborative forecasting, customer relationship management	[25]; [26]; [21]; [18]
	Communications - internal, external	[27]; [25]; [21]; [29];[18]
Organization	Learning, Benchmarking, Feedback	[25];[26];[18]
	Team work, creative problem solving	[25];[26];[18]
Market Position	Market share	[27]; [25]
	Customer relationship	[25];[18]
Security	Layered defenses	[27];[25];[26]
	Cyber security	[27];[25];[26]
Financial strength	Financial reserves & liquidity	[25]
	Price margin	[25]

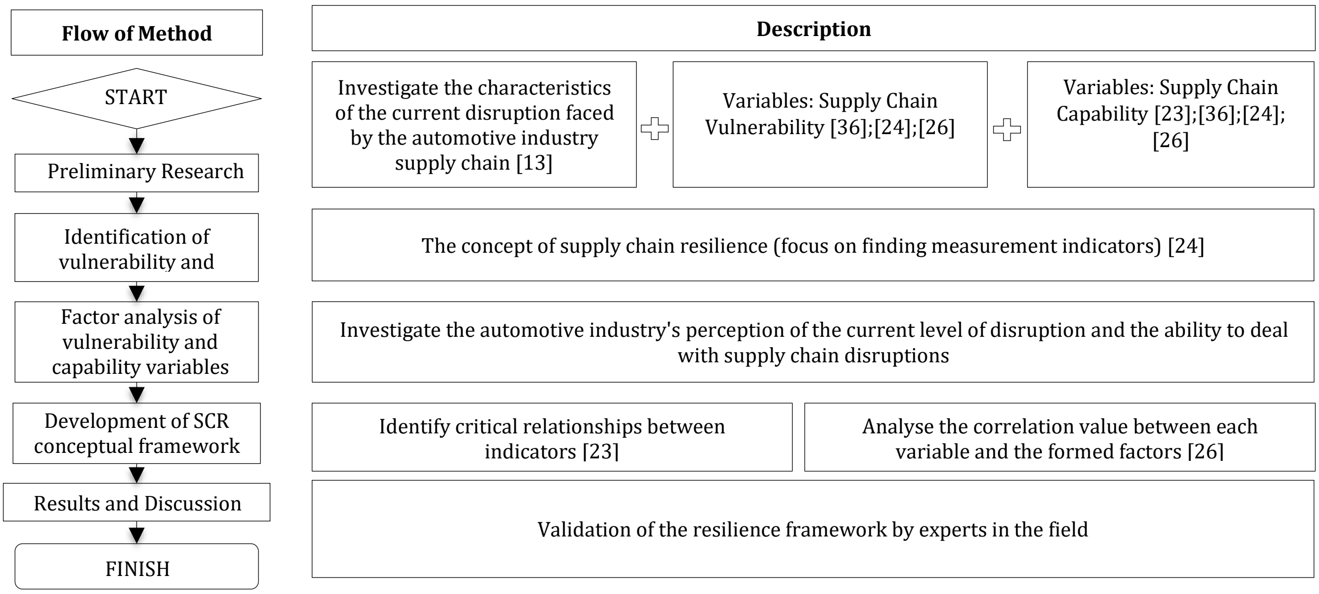

Figure 1. Research framework

2.4. Factor analysis

Factor analysis is a multivariate statistical technique applied to a set of variables when the researcher is interested in determining which variables in the set form logical subsets that are relatively independent [33]. In other words, factor analysis is useful for identifying the factors that underlie variables by grouping related variables within the same factor [34]. In this study, the main focus is applied to factor analysis to reduce a large number of correlated measures into several representative constructs or factors that can be used for further analysis. This factor analysis aims to test the application of the questionnaire item factor analysis to measure vulnerability and capability. Factor analysis is based on the assumption that all variables are correlated to some degree. Therefore, variables must be measured at least at the ordinal level.

The sample size for factor analysis should be larger, but a more acceptable range is a ratio of ten to one [35]. There are two main approaches to factor analysis: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Exploratory factor analysis is used to examine dimensions and is often used in the early stages of research to gather information about the interrelationships between a set of variables [36]. On the other hand, confirmatory factor analysis is a more complex and sophisticated set of techniques used in the research process to test a particular hypothesis or theory regarding the underlying structure of a set of variables [36].

3. Methodology

This study used an exploratory, descriptive research design with a mixed methods research type, using expert judgment or perception in describing, explaining and interpreting a phenomenon that occurs in an object using questionnaires and model validation through focus group discussions (FGD). This research builds a framework for supply chain resilience during the COVID-19 pandemic. In this study, the respondents for the supply chain resilience assessment (SCRAM) questionnaire were 51 employees of the leading automotive industry in Indonesia. The assessment on the SCRAM questionnaire will be used for processing factor analysis data using SPSS software. An overview of the research framework can be seen in Fig. 1.

4. Results and discussion

This study uses exploratory factor analysis to examine data sets to identify complex interrelationships between items and group items that are part of the integrated concept. This study uses factor analysis with principal component extraction to test whether the statement represents identifiable factors related to supply chain resilience. Principal component analysis (PCA) denotes the statistical process used to highlight the variation in which the principal data components are calculated and elicit strong patterns in the data set [37]. The requirements in factor analysis according to [38] are:

1. Kaiser-Mayer-Oikin Measure of Sampling Adequacy (KMO MSA) > 0.5 and Barlett's Test of Sphericity (Sig.) < 0.5.
2. There is a strong correlation between variables, indicated by the value of Anti-Image Correlation between variables > 0.5.

The results of the vulnerability factor analysis obtained from the SPSS software are presented in Table A1 through Table A6 (see Appendices). Table A1 shows that the KMO MSA value is 0.774 > 0.5 and Bartlett's Test of Sphericity (Sig.) value is 0.000 < 0.05, then the factor analysis in this study can be continued because it has met the requirements. MSA > 0.50. Table A2 shows that the MSA value for all variables is the MSA value > 0.50, so all variables are eligible for factor analysis. Based on Table A3, it is known that the extraction value for the variables V1.1, V2.3, and V4.1 is less than 0.50. Thus, all variables can be used to explain factors except for V1.1, V2.3, and V4.1. The Initial Eigenvalues variant shows the formed factors, while the Extraction Sums of Squared Loadings section shows the number of variations or factors that can be formed.

In Table A4, there are three variations of factors, namely 4.729 to 1.237. Green box explanation: based on the Initial Eigenvalues table, three factors can be formed from 11 variables, where the requirement to be a factor, then the Eigenvalue must be > 1. If factors 1 to factor 3 are added up, it can explain 57.332% variation. Table A5 shows the correlation value between each variable and the formed factors. It can be seen in V2.1 that the correlation value of this variable with a factor of 1 is 0.809. A variable belongs to which factor group can be determined by looking at the largest correlation value between the variables and the formed factors (for example variable V1.2). The correlation value of this variable with factor 1 = 0.752 is the largest correlation value of other factors, so the variable V1.2 belongs to the group of factors 1.

Table 3.
List of experts from the leading automotive industry

Expert	Experience	Position
Expert 1	30 Years	General Manager Production
Expert 2	22 Years	Asst. General Manager Logistic
Expert 3	25 Years	Manager Purchasing

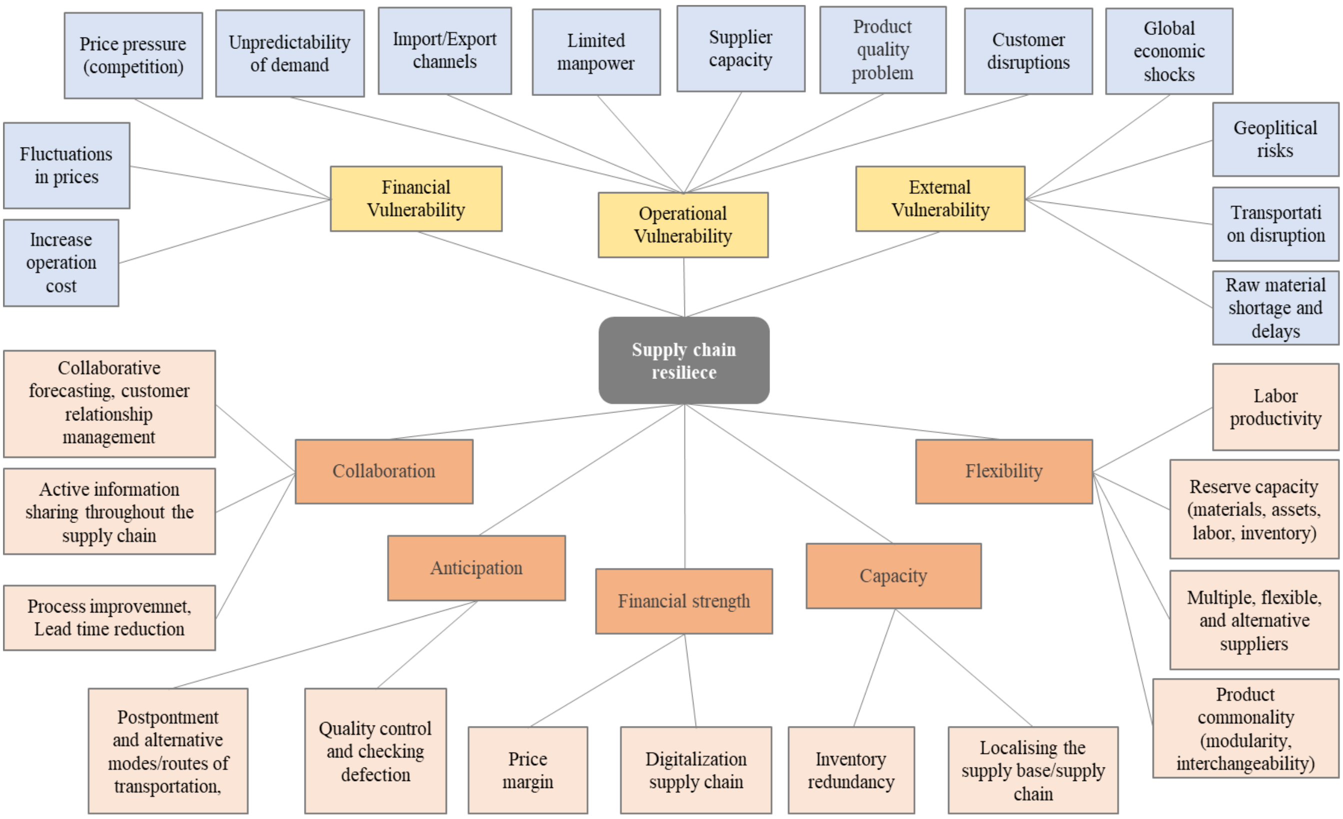

Figure 2. Supply chain resilience framework

At the same time, the results of the capability factor analysis obtained from the SPSS software are presented in Table A7 through Table A12 (see Appendices). Table A7 shows that the KMO MSA value is 0.783 > 0.5 and Bartlett's Test of Sphericity (Sig.) value is 0.000 < 0.05, so the factor analysis in this study can be continued because it meets the requirements. The requirement must be met in the factor analysis is the MSA value > 0.50. From the results of Table A8, it is known that if the MSA value for all variables MSA value > 0.50, then all variables are eligible for factor analysis.

Table A9 shows that the extraction values for the variables C3.1, C.52, C6.2, C7.1, C8.1, C10.1, and C12.2 are smaller than 0.50. Thus, it can be concluded that all variables can be used to explain factors except for variables C3.1, C.52, C6.2, C7.1, C8.1, C10.1, and C12.2. The Initial Eigenvalues variant shows the formed factors, while the Extraction Sums of Squared Loadings section shows the number of variations or factors that can be formed. In the output results above, there are six variations of factors, namely 9.368 to 1.029. Explanation of the green box: based on the Initial Eigenvalues table, six factors can be formed from 24 variables; where the condition is to be a factor, the eigenvalue must be > 1. Therefore, if factors 1 to 6 are added up, it can explain 71.230% of the variation, as shown in Table A11. Table A10 shows the correlation value between each variable and the formed factors. For example, it can be seen in C12.1 that the correlation value of this variable with a factor of 1 is 0.754. To ensure that a variable belongs to which factor group, it can be determined by looking at the largest correlation value between the variable and the formed component. Example: variable C9.1. The correlation value of this variable with factor 1 = 0.744 is the largest correlation value of other factors, so the variable C9.1 belongs to the factor 1 group, as shown in Table A12.

The last step in factor analysis is validation by experts in the automotive industry. The criteria for the selected experts are shown in Table 3. Meanwhile, the results of the validation of vulnerability and capability indicators from the results of focus group discussions (FGD) with experts are shown in Fig. 2. So, there are some variables eliminated and added.

5. Conclusions

The preparation of the supply chain resilience framework is based on determining the dimensions taken from the two basic concepts of this research, namely supply chain vulnerability and supply chain capability. After conducting all stages of research using a factor analysis approach and expert validation, it was found that the vulnerability variable has three factors, namely (i) financial vulnerability, (ii) operational vulnerability, and (iii) external vulnerability, then the three factors are divided into thirteen indicators. While the factors formed from the capability variable are five factors, namely (i) collaboration, (ii) anticipation, (iii) financial strength, (iv) capacity, and (v) flexibility, then the five factors are divided into thirteen indicators. Per the research objectives, grouping and simplifying these priority factors can become a reference for researchers or companies to manage supply chains that are more resilient to disruptions during the COVID-19 pandemic effectively and efficiently.

The weakness of this study is that the respondents are only automotive industry practitioners. It would be more comprehensive if the respondents or experts for validating the supply-chain resilience framework model also come from the government, such as the ministry of industry, and automotive industry associations such as Gaikindo. The next research is to weigh the vulnerability indicators to determine the priority of disturbances and develop strategies using a quality function deployment (QFD) approach to reduce these disturbances so that the supply chain becomes more resilient to disruptions during the COVID-19 pandemic effectively and efficiently.

Declarations statement

S. Sudarto: **Conceptualization, Methodology, Supervision**. M. Syahri Nur Afif: **Software, Writing, & Editing**. M. Ibrahim Ats Tsauri, Hery Sumardiyanto: **Resources, Validation**. H. Sumardiyanto: **Writing - Review & Editing**.

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Appendices

Table A1.
KMO and Bartlett's test vulnerability indicator

Test	Statistics	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	-	0.774
Bartlett's Test of Sphericity	Approx. Chi-Square	223.837
	df	78
	Sig.	0

Table A2.
Anti-image matrices of vulnerability indicators

		V1.1	V1.2	V1.3	V2.1	V2.2	V2.3	V2.4	V2.5	V2.6	V3.1	V3.2	V4.1	V4.2
Anti-image Covariance	V1.1	0.729	-0.215	0.06	-0.011	-0.003	-0.035	0.051	-0.037	-0.109	-0.017	0.038	-0.076	0.035
	V1.2	-0.215	0.482	-0.164	-0.069	-0.022	0.058	-0.107	0.041	-0.039	0.022	-0.105	0.085	-0.055
	V1.3	0.06	-0.164	0.502	-0.102	-0.086	-0.023	0.116	-0.107	0.023	0.047	0.1	-0.074	0.101
	V2.1	-0.011	-0.069	-0.102	0.356	-0.111	0.067	0.007	-0.118	0.019	0.073	-0.102	-0.068	-0.083
	V2.2	-0.003	-0.022	-0.086	-0.111	0.426	-0.165	-0.005	0.103	-0.11	-0.148	-0.097	0.004	-0.07
	V2.3	-0.035	0.058	-0.023	0.067	-0.165	0.479	-0.072	-0.114	0.014	0.145	-0.127	-0.02	-0.146
	V2.4	0.051	-0.107	0.116	0.007	-0.005	-0.072	0.457	-0.187	-0.134	-0.09	0.025	0.038	0.072
	V2.5	-0.037	0.041	-0.107	-0.118	0.103	-0.114	-0.187	0.323	-0.003	-0.13	0.005	-0.056	-0.016
	V2.6	-0.109	-0.039	0.023	0.019	-0.11	0.014	-0.134	-0.003	0.682	0.047	-0.066	-0.02	0.111
	V3.1	-0.017	0.022	0.047	0.073	-0.148	0.145	-0.09	-0.13	0.047	0.747	0.031	-0.054	-0.104
	V3.2	0.038	-0.105	0.1	-0.102	-0.097	-0.127	0.025	0.005	-0.066	0.031	0.553	-0.064	0.181
	V4.1	-0.076	0.085	-0.074	-0.068	0.004	-0.02	0.038	-0.056	-0.02	-0.054	-0.064	0.712	-0.136
	V4.2	0.035	-0.055	0.101	-0.083	-0.07	-0.146	0.072	-0.016	0.111	-0.104	0.181	-0.136	0.701
Anti-image Correlation	V1.1	.797a	-0.363	0.099	-0.022	-0.005	-0.059	0.089	-0.075	-0.154	-0.022	0.059	-0.106	0.05
	V1.2	-0.363	.790a	-0.334	-0.167	-0.048	0.12	-0.227	0.104	-0.068	0.036	-0.204	0.145	-0.095
	V1.3	0.099	-0.334	.763a	-0.241	-0.187	-0.046	0.241	-0.267	0.039	0.077	0.19	-0.124	0.17
	V2.1	-0.022	-0.167	-0.241	.840a	-0.286	0.163	0.017	-0.349	0.038	0.141	-0.23	-0.135	-0.166
	V2.2	-0.005	-0.048	-0.187	-0.286	.789a	-0.365	-0.012	0.277	-0.203	-0.262	-0.2	0.007	-0.128
	V2.3	-0.059	0.12	-0.046	0.163	-0.365	.770a	-0.153	-0.291	0.025	0.242	-0.247	-0.034	-0.251
	V2.4	0.089	-0.227	0.241	0.017	-0.012	-0.153	.735a	-0.486	-0.24	-0.154	0.05	0.067	0.127
	V2.5	-0.075	0.104	-0.267	-0.349	0.277	-0.291	-0.486	.744a	-0.007	-0.265	0.012	-0.118	-0.033
	V2.6	-0.154	-0.068	0.039	0.038	-0.203	0.025	-0.24	-0.007	.842a	0.065	-0.107	-0.029	0.16
	V3.1	-0.022	0.036	0.077	0.141	-0.262	0.242	-0.154	-0.265	0.065	.567a	0.048	-0.075	-0.143
	V3.2	0.059	-0.204	0.19	-0.23	-0.2	-0.247	0.05	0.012	-0.107	0.048	.792a	-0.101	0.29
	V4.1	-0.106	0.145	-0.124	-0.135	0.007	-0.034	0.067	-0.118	-0.029	-0.075	-0.101	.869a	-0.193
	V4.2	0.05	-0.095	0.17	-0.166	-0.128	-0.251	0.127	-0.033	0.16	-0.143	0.29	-0.193	.564a

a. Measures of Sampling Adequacy (MSA)

Table A3.
Communalities vulnerability indicator

Factors	Initial	Extraction
V1.1	1	0.312
V1.2	1	0.583
V1.3	1	0.544
V2.1	1	0.713
V2.2	1	0.576
V2.3	1	0.477
V2.4	1	0.765
V2.5	1	0.712
V2.6	1	0.576
V3.1	1	0.587
V3.2	1	0.521
V4.1	1	0.463
V4.2	1	0.625

Extraction Method: Principal Component Analysis

Table A4.
Total variance explained vulnerability indicator

Component	Initial eigen value			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cummulative %	Total	% of variance	Cummulative %	Total	% of variance	Cummulative %
1	4.729	36.378	36.378	4.729	36.378	36.378	3.509	26.993	26.993
2	1.487	11.435	47.813	1.487	11.435	47.813	2.071	15.929	42.922
3	1.237	9.519	57.332	1.237	9.519	57.332	1.873	14.411	57.332
4	0.976	7.511	64.843						
5	0.849	6.534	71.377						
6	0.747	5.743	77.119						
7	0.726	5.581	82.701						
8	0.594	4.568	87.269						
9	0.509	3.919	91.188						
10	0.381	2.931	94.119						
11	0.34	2.616	96.735						
12	0.239	1.841	98.576						
13	0.185	1.424	100						

Extraction Method: Principal Component Analysis

Table A5.
Component matrix vulnerability indicator

	Component		
	1	2	3
V2.1	0.809		-0.239
V2.5	0.748	0.25	0.299
V2.2	0.733		-0.195
V2.3	0.679	0.125	
V1.2	0.675	-0.333	-0.125
V1.3	0.634		-0.377
V3.2	0.612	-0.368	-0.105
V4.1	0.52	0.384	-0.213
V2.6	0.506	-0.462	0.326
V1.1	0.484	-0.279	
V4.2	0.281	0.697	-0.244
V2.4	0.605		0.632
V3.1	0.283	0.485	0.522

"Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization."
a. Rotation converged in 7 iterations.

Table A6.
Rotated component matrix vulnerability indicator

	Component		
	1	2	3
V1.2	0.752	0.11	
V3.2	0.718		
V2.1	0.659	0.507	0.147
V2.2	0.629	0.404	0.134
V2.6	0.612	-0.28	0.351
V1.3	0.574	0.46	
V1.1	0.545		0.121
V2.3	0.469	0.409	0.3
V4.2	-0.141	0.768	0.12
V4.1	0.225	0.624	0.152
V2.4	0.362		0.795
V3.1	-0.153	0.238	0.712
V2.5	0.392	0.376	0.645

Table A7.
KMO and Bartlett's test vulnerability indicator

Test	Statistics	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	-	0.783
Bartlett's Test of Sphericity	Approx. Chi-Square	729.667
	df	276
	Sig.	0

Table A8.
Anti-image matrices capability indicator

		C1.1	C1.2	C2.1	C3.1	C3.2	C3.3	C4.1	C5.1	C5.2	C6.1	C6.2	C6.3	C7.1	C8.1	C9.1	C9.2	C10.1	C10.2	C11.1	C11.2	C12.1	C12.2	C13.1	C13.2
Anti-image Covariance	C1.1	0.442	-0.162	-0.045	-0.026	0.043	-0.036	0.013	-0.027	-0.064	-0.083	-0.06	0.049	-0.016	-0.015	-0.062	0.085	-0.062	-0.048	0.005	0.086	-0.046	0.016	0.007	0.023
	C1.2	-0.162	0.541	0.027	-0.016	-0.038	0.1	-0.14	0.034	0.04	-0.007	-0.01	-0.018	0.067	0.036	0.072	-0.076	0.042	0.04	-0.052	-0.018	-0.026	0.004	0.013	0.011
	C2.1	-0.045	0.027	0.345	-0.12	-0.045	-0.103	0.092	0.022	0.053	0.115	-0.02	-0.028	0.045	-0.195	0.072	-0.079	0.095	0.034	0.013	-0.012	-0.056	-0.033	-0.088	0.047
	C3.1	-0.026	-0.016	-0.12	0.264	-0.142	0.067	-0.091	-0.005	-0.096	-0.041	0.039	0.018	-0.073	0.124	0.033	0.016	-0.093	0.035	-0.027	-0.037	0.008	0.063	0.087	-0.041
	C3.2	0.043	-0.038	-0.045	-0.142	0.342	-0.012	0.031	-0.013	0.082	-0.064	-0.032	-0.012	0.02	-0.092	-0.111	0.056	0.008	-0.058	0.007	0.084	0.011	-0.109	-0.002	0.018
	C3.3	-0.036	0.1	-0.103	0.067	-0.012	0.361	-0.126	0.039	-0.003	-0.043	0.022	-0.062	0.026	0.072	-0.069	0.021	0.023	-0.039	-0.059	-0.027	0.041	-0.031	0.037	-0.027
	C4.1	0.013	-0.14	0.092	-0.091	0.031	-0.126	0.249	-0.064	0.014	0.044	-0.049	0.004	0.014	-0.135	-0.031	-0.037	0.034	0.023	0.021	0.052	-0.002	-0.053	-0.003	-0.002
	C5.1	-0.027	0.034	0.022	-0.005	-0.013	0.039	-0.064	0.3	-0.059	-0.04	0.035	0.041	-0.069	0.071	-0.003	-0.025	0.024	-0.015	-0.046	-0.057	-0.034	0.019	-0.042	0.022
	C5.2	-0.064	0.04	0.053	-0.096	0.082	-0.003	0.014	-0.059	0.315	0.054	-0.061	0.018	-0.004	-0.087	-0.039	0.025	0.043	0.014	-0.072	0.045	-0.015	-0.102	-0.08	0.059
	C6.1	-0.083	-0.007	0.115	-0.041	-0.064	-0.043	0.044	-0.04	0.054	0.372	-0.074	0.024	0.014	-0.067	0.074	-0.094	0.084	0.088	-0.049	-0.082	-0.027	0.006	-0.028	0.014
	C6.2	-0.06	-0.01	-0.02	0.039	-0.032	0.022	-0.049	0.035	-0.061	-0.074	0.22	-0.127	0.013	0.045	-0.041	0.045	0.032	-0.081	0.038	-0.044	0.075	0.032	-0.011	-0.096
	C6.3	0.049	-0.018	-0.028	0.018	-0.012	-0.062	0.004	0.041	0.018	0.024	-0.127	0.205	-0.088	0.035	0.057	-0.019	-0.064	0.076	-0.063	-0.004	-0.092	-0.004	0.003	0.074
	C7.1	-0.016	0.067	0.045	-0.073	0.02	0.026	0.014	-0.069	-0.004	0.014	0.013	-0.088	0.25	-0.06	-0.019	-0.051	0.017	-0.007	-0.052	0.085	0.026	-0.058	0.012	-0.038
	C8.1	-0.015	0.036	-0.195	0.124	-0.092	0.072	-0.135	0.071	-0.087	-0.067	0.045	0.035	-0.06	0.426	-0.001	0.019	-0.055	-0.04	0.02	-0.073	0.015	0.054	0.055	-0.018
	C9.1	-0.062	0.072	0.072	0.033	-0.111	-0.069	-0.031	-0.003	-0.039	0.074	-0.041	0.057	-0.019	-0.001	0.24	-0.096	-0.022	0.087	-0.013	-0.008	-0.108	0.046	-0.046	0.067
	C9.2	0.085	-0.076	-0.079	0.016	0.056	0.021	-0.037	-0.025	0.025	-0.094	0.045	-0.019	-0.051	0.019	-0.096	0.154	-0.029	-0.081	0.054	-0.014	0.029	-0.004	-0.023	-0.026
	C10.1	-0.062	0.042	0.095	-0.093	0.008	0.023	0.034	0.024	0.043	0.084	0.032	-0.064	0.017	-0.055	-0.022	-0.029	0.272	-0.103	0.031	-0.056	-0.004	0.009	-0.04	-0.036
	C10.2	-0.048	0.04	0.034	0.035	-0.058	-0.039	0.023	-0.015	0.014	0.088	-0.081	0.076	-0.007	-0.04	0.087	-0.081	-0.103	0.213	-0.095	0.018	-0.053	-0.011	-0.007	0.037
	C11.1	0.005	-0.052	0.013	-0.027	0.007	-0.059	0.021	-0.046	-0.072	-0.049	0.038	-0.063	-0.052	0.02	-0.013	0.054	0.031	-0.095	0.238	-0.072	0.042	0.054	-0.018	-0.005
	C11.2	0.086	-0.018	-0.012	-0.037	0.084	-0.027	0.052	-0.057	0.045	-0.082	-0.044	-0.004	0.085	-0.073	-0.008	-0.014	-0.056	0.018	-0.072	0.22	-0.057	-0.085	-0.009	0.026
	C12.1	-0.046	-0.026	-0.056	0.008	0.011	0.041	-0.002	-0.034	-0.015	-0.027	0.075	-0.092	0.026	0.015	-0.108	0.029	-0.004	-0.053	0.042	-0.057	0.27	-0.024	0.062	-0.126
	C12.2	0.016	0.004	-0.033	0.063	-0.109	-0.031	-0.053	0.019	-0.102	0.006	0.032	-0.004	-0.058	0.054	0.046	-0.004	0.009	-0.011	0.054	-0.085	-0.024	0.322	-0.03	-0.068
	C13.1	0.007	0.013	-0.088	0.087	-0.002	0.037	-0.003	-0.042	-0.08	-0.028	-0.011	0.003	0.012	0.055	-0.046	-0.023	-0.04	-0.007	-0.018	-0.009	0.062	-0.03	0.306	-0.12
	C13.2	0.023	0.011	0.047	-0.041	0.018	-0.027	-0.002	0.022	0.059	0.014	-0.096	0.074	-0.038	-0.018	0.067	-0.026	-0.036	0.037	-0.005	0.026	-0.126	-0.068	-0.12	0.296
Anti-image Correlation	C1.1	.712a	-0.331	-0.116	-0.077	0.111	-0.091	0.04	-0.074	-0.171	-0.205	-0.192	0.163	-0.047	-0.035	-0.191	0.327	-0.179	-0.158	0.016	0.277	-0.132	0.043	0.02	0.065
	C1.2	-0.331	.601a	0.062	-0.043	-0.089	0.225	-0.381	0.085	0.098	-0.016	-0.03	-0.053	0.183	0.075	0.199	-0.264	0.11	0.119	-0.145	-0.051	-0.068	0.009	0.032	0.028
	C2.1	-0.116	0.062	.541a	-0.397	-0.131	-0.292	0.313	0.068	0.161	0.322	-0.072	-0.106	0.155	-0.508	0.25	-0.342	0.31	0.125	0.045	-0.044	-0.185	-0.1	-0.271	0.146
	C3.1	-0.077	-0.043	-0.397	.659a	-0.472	0.217	-0.355	-0.018	-0.334	-0.131	0.16	0.079	-0.282	0.37	0.13	0.08	-0.348	0.146	-0.108	-0.154	0.029	0.215	0.306	-0.146
	C3.2	0.111	-0.089	-0.131	-0.472	.752a	-0.035	0.106	-0.041	0.249	-0.179	-0.116	-0.045	0.067	-0.24	-0.387	0.244	0.026	-0.215	0.024	0.305	0.037	-0.329	-0.007	0.057
	C3.3	-0.091	0.225	-0.292	0.217	-0.035	.837a	-0.419	0.12	-0.009	-0.117	0.077	-0.229	0.085	0.184	-0.235	0.088	0.073	-0.14	-0.2	-0.094	0.132	-0.09	0.111	-0.083
	C4.1	0.04	-0.381	0.313	-0.355	0.106	-0.419	.791a	-0.232	0.048	0.143	-0.209	0.019	0.056	-0.413	-0.127	-0.188	0.129	0.101	0.088	0.221	-0.006	-0.188	-0.01	-0.006
	C5.1	-0.074	0.085	0.068	-0.018	-0.041	0.12	-0.232	.903a	-0.191	-0.119	0.138	0.164	-0.252	0.198	-0.01	-0.118	0.084	-0.06	-0.17	-0.224	-0.119	0.06	-0.139	0.073
	C5.2	-0.171	0.098	0.161	-0.334	0.249	-0.009	0.048	-0.191	.783a	0.157	-0.231	0.072	-0.013	-0.237	-0.142	0.115	0.145	0.053	-0.262	0.171	-0.052	-0.319	-0.257	0.192
	C6.1	-0.205	-0.016	0.322	-0.131	-0.179	-0.117	0.143	-0.119	0.157	.732a	-0.258	0.088	0.047	-0.169	0.249	-0.392	0.264	0.312	-0.165	-0.288	-0.086	0.017	-0.083	0.042
	C6.2	-0.192	-0.03	-0.072	0.16	-0.116	0.077	-0.209	0.138	-0.231	-0.258	.768a	-0.598	0.054	0.146	-0.18	0.243	0.132	-0.374	0.168	-0.2	0.307	0.122	-0.043	-0.377
	C6.3	0.163	-0.053	-0.106	0.079	-0.045	-0.229	0.019	0.164	0.072	0.088	-0.598	.743a	-0.39	0.119	0.259	-0.107	-0.271	0.363	-0.285	-0.018	-0.39	-0.014	0.012	0.302
	C7.1	-0.047	0.183	0.155	-0.282	0.067	0.085	0.056	-0.252	-0.013	0.047	0.054	-0.39	.858a	-0.184	-0.077	-0.259	0.066	-0.03	-0.212	0.362	0.098	-0.206	0.042	-0.141
	C8.1	-0.035	0.075	-0.508	0.37	-0.24	0.184	-0.413	0.198	-0.237	-0.169	0.146	0.119	-0.184	.641a	-0.003	0.073	-0.161	-0.132	0.062	-0.24	0.043	0.147	0.152	-0.05
	C9.1	-0.191	0.199	0.25	0.13	-0.387	-0.235	-0.127	-0.01	-0.142	0.249	-0.18	0.259	-0.077	-0.003	.751a	-0.498	-0.085	0.383	-0.053	-0.033	-0.426	0.165	-0.169	0.25
	C9.2	0.327	-0.264	-0.342	0.08	0.244	0.088	-0.188	-0.118	0.115	-0.392	0.243	-0.107	-0.259	0.073	-0.498	.778a	-0.143	-0.446	0.281	-0.078	0.141	-0.019	-0.104	-0.123
	C10.1	-0.179	0.11	0.31	-0.348	0.026	0.073	0.129	0.084	0.145	0.264	0.132	-0.271	0.066	-0.161	-0.085	-0.143	.802a	-0.427	0.121	-0.228	-0.014	0.031	-0.14	-0.129

continued

Table A8.
Anti-image matrices capability indicator (*continued*)

		C1.1	C1.2	C2.1	C3.1	C3.2	C3.3	C4.1	C5.1	C5.2	C6.1	C6.2	C6.3	C7.1	C8.1	C9.1	C9.2	C10.1	C10.2	C11.1	C11.2	C12.1	C12.2	C13.1	C13.2
Anti-image Covariance	C10.2	-0.158	0.119	0.125	0.146	-0.215	-0.14	0.101	-0.06	0.053	0.312	-0.374	0.363	-0.03	-0.132	0.383	-0.446	-0.427	.748a	-0.423	0.081	-0.221	-0.042	-0.027	0.146
	C11.1	0.016	-0.145	0.045	-0.108	0.024	-0.2	0.088	-0.17	-0.262	-0.165	0.168	-0.285	-0.212	0.062	-0.053	0.281	0.121	-0.423	.826a	-0.317	0.164	0.195	-0.068	-0.02
	C11.2	0.277	-0.051	-0.044	-0.154	0.305	-0.094	0.221	-0.224	0.171	-0.288	-0.2	-0.018	0.362	-0.24	-0.033	-0.078	-0.228	0.081	-0.317	.790a	-0.235	-0.32	-0.037	0.102
	C12.1	-0.132	-0.068	-0.185	0.029	0.037	0.132	-0.006	-0.119	-0.052	-0.086	0.307	-0.39	0.098	0.043	-0.426	0.141	-0.014	-0.221	0.164	-0.235	.831a	-0.083	0.217	-0.447
	C12.2	0.043	0.009	-0.1	0.215	-0.329	-0.09	-0.188	0.06	-0.319	0.017	0.122	-0.014	-0.206	0.147	0.165	-0.019	0.031	-0.042	0.195	-0.32	-0.083	.879a	-0.094	-0.22
	C13.1	0.02	0.032	-0.271	0.306	-0.007	0.111	-0.01	-0.139	-0.257	-0.083	-0.043	0.012	0.042	0.152	-0.169	-0.104	-0.14	-0.027	-0.068	-0.037	0.217	-0.094	.876a	-0.398
	C13.2	0.065	0.028	0.146	-0.146	0.057	-0.083	-0.006	0.073	0.192	0.042	-0.377	0.302	-0.141	-0.05	0.25	-0.123	-0.129	0.146	-0.02	0.102	-0.447	-0.22	-0.398	.819a

a. Measures of Sampling Adequacy (MSA)

Table A9.
Communalities capability indicator

Factors	Initial	Extraction
C1.1	1	0.559
C1.2	1	0.728
C2.1	1	0.749
C3.1	1	0.485
C3.2	1	0.685
C3.3	1	0.713
C4.1	1	0.777
C5.1	1	0.721
C5.2	1	0.457
C6.1	1	0.695
C6.2	1	0.413
C6.3	1	0.758
C7.1	1	0.465
C8.1	1	0.384
C9.1	1	0.724
C9.2	1	0.826
C10.1	1	0.412
C10.2	1	0.728
C11.1	1	0,780
C11.2	1	0.788
C12.1	1	0.641
C12.2	1	0.376
C13.1	1	0.705
C13.2	1	0.595

Extraction Method: Principal Component Analysis

Table A10.
Total variance explained capability indicator

Component	Initial eigen value			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cummulative %	Total	% of variance	Cummulative %	Total	% of variance	Cummulative %
1	9.368	39.033	39.033	9.368	39.033	39.033	3.455	14.396	14.396
2	2.245	9.352	48.385	2.245	9.352	48.385	3.355	13.978	28.374
3	1.648	6.867	55.253	1.648	6.867	55.253	3.353	13.973	42.347
4	1.487	6.197	61.45	1.487	6.197	61.45	3.09	12.875	55.222
5	1.318	5.491	66.941	1.318	5.491	66.941	2.211	9.214	64.436
6	1.029	4.289	71.23	1.029	4.289	71.23	1.631	6.794	71.23
7	0.92	3.835	75.065						
8	0.814	3.392	78.456						
9	0.73	3.043	81.5						
10	0.624	2.599	84.099						
11	0.558	2.323	86.422						
12	0.481	2.006	88.428						
13	0.466	1.943	90.371						
14	0.399	1.663	92.033						
15	0.365	1.521	93.555						
16	0.307	1.277	94.832						
17	0.266	1.108	95.94						
18	0.234	0.974	96.914						
19	0.191	0.794	97.708						
20	0.165	0.686	98.393						
21	0.126	0.524	98.917						
22	0.105	0.436	99.353						
23	0.09	0.377	99.73						
24	0.065	0.27	100						

Extraction Method: Principal Component Analysis

Table A11.
Component matrix capability indicator

	Component					
	1	2	3	4	5	6
C12.1	0.754	-0.216	0.081	-0.052	0.071	0.108
C12.2	0.751	-0.196	0.082	0.011	0.03	-0.18
C9.2	0.735	-0.376	0.051	-0.196	0.32	0.041
C7.1	0.734	0.237	-0.124	-0.204	-0.118	0.013
C13.1	0.699	-0.294	-0.212	-0.132	0.107	-0.239
C13.2	0.697	-0.29	-0.06	-0.095	0.115	0.004
C6.2	0.696	0.096	-0.151	0.385	-0.196	-0.13
C5.1	0.694	0.195	-0.284	-0.212	0.27	0.042
C10.2	0.687	-0.183	-0.175	-0.299	-0.254	0.193
C9.1	0.681	0.071	0.101	-0.311	0.234	-0.306
C4.1	0.673	0.32	0.255	-0.027	0.341	-0.2
C11.1	0.671	0.241	-0.4	0.195	-0.239	0.13
C6.3	0.661	-0.026	-0.123	0.45	-0.32	0.026
C3.3	0.651	-0.003	0.054	0.313	-0.148	-0.408
C11.2	0.646	-0.448	-0.169	0.307	0.074	0.201
C10.1	0.621	-0.27	-0.115	-0.379	-0.213	0.377
C3.2	0.562	0.257	0.508	-0.051	-0.194	0.075
C5.2	0.553	0.525	-0.209	-0.135	-0.136	-0.271
C6.1	0.532	-0.017	-0.115	0.491	0.369	0.144
C3.1	0.518	0.504	0.238	-0.077	-0.12	0.399
C1.1	0.36	0.643	0.05	-0.079	-0.085	0.024
C2.1	0.372	-0.32	0.615	0.201	-0.299	-0.014
C8.1	0.448	-0.21	0.575	-0.101	-0.091	-0.046
C1.2	0.267	0.34	0.237	0.31	0.53	0.329

Extraction Method: Principal Component Analysis
a. 6 components extracted

Table A12.
Rotated component matrix capability indicator

	Component					
	1	2	3	4	5	6
C9.1	0.744	0.187	0.059	0.319	0.168	0.042
C13.1	0.645	0.41	0.343	-0.025	0.034	-0.043
C9.2	0.627	0.548	0.104	-0.071	0.227	0.255
C4.1	0.608	-0.024	0.135	0.458	0.232	0.352
C12.2	0.537	0.309	0.382	0.087	0.316	0.071
C5.1	0.519	0.408	0.176	0.397	-0.205	0.234
C10.1	0.144	0.85	0.086	0.154	0.159	-0.063
C10.2	0.234	0.73	0.241	0.223	0.123	-0.132
C12.1	0.408	0.507	0.269	0.1	0.301	0.212
C13.2	0.487	0.494	0.267	-0.002	0.164	0.125
C6.3	0.037	0.253	0.785	0.169	0.199	0.092
C6.2	0.217	0.144	0.75	0.262	0.115	0.094
C3.3	0.417	-0.036	0.652	0.161	0.293	-0.029
C11.1	0.069	0.377	0.643	0.436	-0.151	0.083
C11.2	0.219	0.522	0.541	-0.24	0.131	0.315
C1.1	0.074	-0.029	0.1	0.73	0.004	0.096
C3.1	-0.073	0.279	0.06	0.72	0.252	0.301
C5.2	0.364	0.037	0.323	0.68	-0.131	-0.133
C7.1	0.353	0.409	0.285	0.539	0.048	-0.003
C2.1	0.023	0.103	0.238	-0.079	0.822	0.007
C8.1	0.266	0.178	0.008	0.067	0.699	0.029
C3.2	0.128	0.136	0.111	0.526	0.589	0.121
C1.2	0.065	-0.079	0.007	0.245	0.066	0.808
C6.1	0.229	0.129	0.489	-0.019	-0.025	0.621

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 19 iterations