Factor Analysis to Evaluate Hospital Resilience

FACTOR ANALYSIS TO EVALUATE HOSPITAL RESILIENCE

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ABSTRACT

Healthcare facilities should be able to adapt to catastrophic events such as natural and manmade disasters quickly. One way to reduce the impacts of extreme events is to enhance hospital's resilience. Resilience is defined as the ability to absorb and recover from hazardous events, containing the effects of disasters when they occur. The goal of this paper is to propose a fast methodology for quantifying disaster resilience of healthcare facilities. The evaluation of disaster resilience has been conducted on empirical data from tertiary hospitals in the San Francisco Bay Area. A survey has been conducted during a four months period using ad hoc questionnaire. The collected data have been analyzed using factor analysis. A combination of variables has been used to describe the characteristics of the hidden factors. Three factors have been identified as most representative of the hospital disaster resilience: (i) *cooperation and training management*, (ii) *resources and equipment capability* and (iii) *structural and organizational operating procedures*. Together they cover 83% of the total variance. The overall level of hospital disaster resilience (R) has been calculated by combining linearly the three extracted factors. This methodology provides a relatively simple way to evaluate hospitals' ability to manage extreme events.

Keywords: *Resilience evaluation, factor analysis, emergency, disaster, hospital, performance*.

INTRODUCTION

Natural and manmade disasters worldwide have constantly increased, becoming more frequent and more intense in the last decade. They also have a greater social and economic impact than before due to the

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increased urbanization level, the environmental degradation and the climate changes (e.g. higher temperatures or extreme precipitations). Generally, healthcare facilities and emergency services have to manage a sudden inflow of patients due to major disasters that can bring the entire system to collapse. Hospitals are different from other healthcare organizations because they play an important role in the aftermath of an emergency by providing continued access to care, therefore they belong to that group of infrastructure called lifelines. In order to allow the hospitals to perform as expected during the emergencies, it is necessary to have developed internal concepts and methods that allows to manage this complexity.

Hospital disaster resilience provides this capacity because its focus is on a system's overall ability to prepare and plan for, absorb, recover from catastrophic events as well as sustain required operations under both expected and unexpected conditions. However, hospital's adaptive behaviors depend on several variables, related with the complexity of the system. In fact, *hospital disaster resilience* must be measured separately, using multiple concepts such as hospital safety, cooperation, recovery, emergency plans, business continuity, critical care capacity, and other specific abilities. Thus, the overall resilience level of an hospital can be obtained by combining the resilience of each individual variable in order to take into account hospital's response ability at all levels of the system (Zhong, 2014).

Recently several methods has been proposed to measure the hospital's ability to provide emergency care to all the injured in an extreme situation. In this study, a framework for hospital resilience has been developed, using empirical data from hospitals in the San Francisco Bay Area (California).

To achieve this goal, data from a survey questionnaire (Supplemental DataAppendix A) have been analyzed to determine the key factors to be used to measure hospital resilience. In this work, factor analysis has been used to extract the main components, because it is a type of analysis that is used to describe a characteristic that is not directly observable based on a set of observable variables. Lately, factor analysis has been extensively used to analyze and measure latent factors in different fields as well (Li et al., 2013).

The main reason why Factor Analysis (FA) has been selected is because it is easy to use and accurate, both objective and subjective attributes can be used and because it is characterized in flexibility in naming and using dimensions. However, it is important to emphasize that the final result of factor analytical investigation depends, in part, on the decisions and interpretations of the researchers.

On the other hand, other methods such as Machine Learning techniques can also be adopted to analyze the problem at hand, but it will require to select the proper algorithm because there is no guarantee to always work in every case.

In detail, eight variables have been selected as the most representative ones to describe the hospital's performance during an emergency. Three factors explaining over 80% of variance have been found, including (i) *cooperation and training management*, (ii) *resources and equipment capability*, (iii) *structural and organizational operating procedures*. Each of these factors can be analyzed separately, to understand which part of the hospital's internal system needs to be improved. Then, score models have been established to measure the level of hospital disaster resilience. The model provides an analytical expression for hospital resilience (R), combining linearly the three extracted factors. The weight for each factor has been obtained and the overall resilience for the considered hospitals has been estimated.

STATE OF ART

Factor analysis is a multivariate statistical approach commonly used to investigate how many latent variables underlie a set of items. Historically factor analysis has been used primarily in psychology and education; however its use within the health science sector has become much more common during the past two decades (Williams et al., 2010). Reducing the data to a smaller set of variables could help understanding some aspects of the hospitals' behavior during an emergency. Indeed, the primary aim of hospital's planners during a crisis should not be trying to create plans for ever more contingencies, since contingencies are numerous, but rather to create capabilities for resilience (Stenberg, 2003). Bruneau et al. (2003) define a resilient system as a system which reduces failure probabilities, limits consequences from failures and decreases time to restore “normal” level of functional performance. A conceptual understanding of hospital resilience is essential for an integrated approach to enhance hospital resilience to cope with future disasters (Cimellaro et al., 2010, 2016).

Several researchers are aware of the utility to adopt factor analysis to analyze guidelines associated with hospitals emergency management (Pett et al., 2003). For example, O'Malley et al. (2005) has analyzed the quality of care and service in hospitals using factor analysis. They tried to identify the important dimensions of health cares to improve the hospital quality. Cimellaro et al. (2010b) analyzed the seismic resilience of an hospital network located in US using an analytical function which is based on a loss estimation performance indicator.

Later, Nakajima et al., (2012) has analyzed public hospitals in Japan in terms of financial managements, medical services and cost efficiency using factor analysis. They provided also indices to evaluate hospitals financial status and make a comparison in terms of stability between the outcomes from factor analysis and the Date Envelopment Analysis (DEA), a traditional method to evaluate the efficiency of public sectors.

In this paper it is proposed a fast and simple methodology to evaluate the hospitals’ ability to manage extreme events. In particular, the method identifies the main factors that define the hospital resilience during an emergency in order to take actions to increase the overall level of resilience of the hospital system.

METHODOLOGY

In this research, a study has been conducted on Tertiary Hospitals located in the San Francisco Bay Area in California. Tertiary Hospitals are referral hospitals that provide comprehensive and multidisciplinary care which requires highly specialized equipment as well as full departmentalization and facilities with the service capabilities. A questionnaire with 33 questions that is shown in Appendix A has been developed to collect relevant data for the hospitals' resilience analysis. The survey has been conducted between April 2014 and July 2014. Among all the selected hospitals in the San Francisco's Bay Area, 16 complete questionnaires have been collected which represent about a 71% response rate. The location of the hospitals analyzed is shown in Figure 1.

Figure 1

The survey has been conducted by interviewing the hospital's emergency staff or by sending the questionnaire by e-mail. For each hospital a person who is familiar with emergency plan has been selected for filling out the questionnaire (in most cases the Director of the emergency department or someone designated by him). All the selected hospitals have been informed about the research goal and developments. Before starting the factor analysis, the collected questionnaires has been reviewed in order to check their completeness and consistency.

Description of the Questionnaire

The questionnaire consists of 33 questions grouped in 8 sections. All the questions are in multiple choice format, where the only two possible answers are "YES" or "NO". To the option "YES" has been assigned the score "1", to the option "NO" the score "0". The answer "YES" represents the hospital's ability to resist and absorb the shock of disasters, while the answer "NO" is related to a less resilient hospital's behavior. The total score of each section has been obtained by summing the score of each question. The higher the final score, the more resilient is the hospital to disasters.

Eight major variables have been selected to reflect the hospital's behavior during an emergency which are listed below in order to simplify the analysis.

(a) Hospital safety

(b) Hospital disaster leadership and cooperation

(c) Hospital disaster plan

(d) Emergency stockpiles and logistics management

(e) Emergency Staff

(f) Emergency critical care capability

(g) Emergency training and drills

(h) Recovery and reconstruction

All the collected data from the survey has been analyzed to identify a lower number of unobserved variables which reflect the hospital disaster resilience. The data from the questionnaire has been saved in a database and factor analysis has been performed using IBM SPSS Statistic version 21, downloaded on May 15, 2014. The basic idea of the method is to reduce the number of variables included in the hospital's resilience analysis, by including only the significant ones. In fact some of these variables are linearly related each other. Thus, firstly the presence of significant correlations between the items has been checked. Then, initial factor loadings have been calculated using the *Principal Component Method*. Once the initial factor loadings have been calculated, the factors have been rotated to find factors easier to interpret. Rotation goal is to ensure that all the variables have high loadings only on one factor. Varimax rotation has been used to rotate the extracted principal components. Then, factors scores have been obtained and the number of factors have been chosen looking at the number of eigenvalues greater than 1. Finally, a framework for hospital disaster resilience has been obtained as linear combination of the extracted factors, taking into account the calculated weights.

FACTOR ANALYSIS

Factor analysis is a statistical method used to investigate whether a certain number of variables of interest $Y_1, Y_2... Y_n$ are related to a smaller number of unobserved variables $F_1, F_2... F_m$ called factors. A factor is a hypothetical variable that influences the score on one or more observed variables. The factor analysis's first goal is to determine how many factors are necessary to include all the information available in the original set of statements. Different methods exist for estimating the parameters of a factor model. In this research, the *Principal Component method* has been used. It consists in an orthogonal transformation that converts a number of correlated variables into a set of factors that are linearly uncorrelated and with high variance. These factors are called principal components. Therefore, each variable can be expressed as a linear combination of a number of common factors:

$$z_j = k_{j1}F_1 + k_{j2}F_2 + \ldots + k_{jh}F_m \tag{1}$$

where z_j is the j-th standardized variable, $F_1, F_2, \ldots, F_n$ are common factors independent and orthogonal each other (with $m < n$) and k_{jh} are the calculated coefficients. Then, applying the inverse factor model, it is possible to obtain the factors' equations as a linear combination of the original variables:

$$\begin{aligned} F_1 &= c_{11}z_1 + c_{12}z_2 + \ldots + c_{1n}z_n \\ F_2 &= c_{21}z_1 + c_{22}z_2 + \ldots + c_{2n}z_n \\ &\ldots \\ F_m &= c_{m1}z_1 + c_{m2}z_2 + \ldots + c_{mn}z_n \end{aligned} \tag{2}$$

In order to extract the key component factors, three steps have been considered. First, the relationships between variables has been analyzed; second, the factors have been extracted and finally an analytical formula to determine hospitals' resilience has been proposed.

Correlation analysis

As aforementioned, factor analysis' goal is to obtain the factors that can represent the correlation between variables. It means that these variables have to be somehow connected each other. So, if the relationships between variables are weak, it is unlikely that common factors exist. Two tests have been used to verify the presence of significant correlations between the items. The *Kaiser-Meyer-Olkin test* (KMO) is used to check whether the sample is large enough. The sample is adequate when KMO value is greater than 0.5. *Bartlett's test of sphericity* compares the observed correlation matrix to the identity matrix (a matrix of zero correlation). In particular, it checks if the correlation matrix is an identify matrix implying that all of the variables are uncorrelated. In this study, the KMO value is greater than 0.5 and the Bartlett's test indicates that some variables are not independent. These tests suggest that the data are suitable for a factor analysis, as shown in the correlation matrix in Table 1.

Table 1

The correlation matrix shows that some variables are correlated. In fact, the absolute values outside the main diagonal are often close to 1 (e.g. *b* and *d*: 0.813; *g* and *b*: 0.764). This means that these variables are valuable for a factor analysis. Moreover, the table of communalities has been examined to test the goodness of fit. Indeed, this table shows how much of the variance in each of the original variables is explained by the extracted factors. For example in the first row of Table 2 $R^2 = 0.869$ indicates that about 87% of the variation in hospital safety (a) is explained by the factor model. The results in Table 2 suggest that the factor analysis does the best job of explaining variation in variables (b) Hospital disaster leadership and cooperation, (d) Emergency stockpiles and logistics management and (h) Recovery and reconstruction.

Table 2

If the communality for a variable is less than 50%, it is a candidate for exclusion from the analysis because the factor solution contains less than half of the variance in the original variable. For this reason, higher communalities are desirable. In this case, the extracted communalities for all the testing variables are greater than 70%, which indicate that the extracted components represent the variables well.

Factor extraction

The *Principal Component Method* (PCA) has been used to extract the independent factors using the eigenvalues determined by the analysis. The eigenvalues indicate the variance included in each principal component or factor so the sum of the eigenvalues is equal to the number of variables. The number of factors has been determined considering the number of eigenvalues that exceed 1.0, according to the method proposed by Kaiser (1960). In fact, lower values describe less variability than does a single variable. In the case study analyzed, three factors have an eigenvalue greater than 1, as shown in Table 3:

Table 3

The three extracted factors appear to be representative of all the domains and they are arranged in the descending order on the most explained variance. In fact, the cumulative variance of these three factors exceed 83% which means that they are sufficient to describe the hospital's performance.

Truncated component solution

The *initial solution* has as many components (factors) as there are variables (complete components solution shown in the first three columns of Table 3). The extracted solution has the chosen number of factors (*truncated components solution*). The *Component Matrix* shows the correlation between each factor and each variable. It is obtained using the *Principal Factor Analysis* (PFA) that is different from *Principal Component Analysis* (PCA). The defining characteristic that distinguishes between the two factors analytic models is that in PCA it is assumed that all variability in an item should be used in the analysis, while in PFA it is only used the variability in an item that it has in common with the other items. A detailed discussion of the pros and cons of each approach is beyond the scope of this paper, however in most cases, these two methods usually yield very similar results.

Rotating the factor structure

The *Rotation phase* of factor analysis attempts to transform the initial matrix in one that is easier to interpret by rotatin the factor axes. Typical rotational strategies are *varimax, quartimax*, and *equamax*. Varimax rotation has been used in this research to improve results' analysis and interpretability. Shortly, Varimax rotation is an orthogonal rotation developed by Kaiser (1960). Analytically, Varimax searches for a rotation (i.e., a linear combination) of the factors axes to maximize the variance of the squared loadings of a factor (column) on all the variables (rows) in a factor matrix, which means minimize the complexity of the extracted factors. Indeed, the relationship between the initial items and the extracted factors is not clear after the factors' extraction. For this reason, rotation has been used in an effort to find another set of loadings that fit the observations equally well, but can be more easily interpreted. After a Varimax rotation, each original domain tends to be associated with one of the three extracted factors and each factor represents only a small number of items. In fact, the orthogonal rotations keep the factors uncorrelated, while increasing the significance of the factors.

Table 4

A Rotated Component Matrix has been obtained which helps determining the meaning of each factor. The total amount of variation explained by the three factors remains the same and the total amount of variation explained by both models is identical.

Table 4 shows a new set of values for each of the three extracted factors. The boldface values represent the larger correlations of the extracted factor versus the corresponding variable. The first factor is strictly connected to three items, including *hospital disaster leadership and cooperation* (0.947), *emergency stockpiles and logistics management* (0.919), *emergency training and drills* (0.836). Three variables are also included in the second factor that is primarily a *measure of emergency staff* (0.733), *emergency critical care capability* (0.834), *recovery and reconstruction* (0.822). The third factor contains information mainly from two items, *hospital safety* (0.770) and *hospital disaster plan* (0.842). Therefore, some observations have been made. In fact, it is possible to see that all the items have high factor loadings on only one factor.

The first factor (F_1) includes all the items related with the hospital management mechanisms during emergencies. On the other hand, the second factor (F_2) is representative of the emergency department's capability, in terms of human and financial resources as well as hospital's facilities (beds, emergency rooms, etc....). The third factor (F_3) focuses on the hospital's prevention strategies (structural and organizational). In this way, the three extracted factors have been identified and named:

(F_1) Cooperation and Training Management

(F_2) Resources and Equipment Capability

(F_3) Structural and Organizational Operating Procedures

Finally the linear combination of these three factors represents what is called as hospital's resilience.

NUMERICAL RESULTS OF FACTOR ANALYSIS

Each of the variables describing the hospital's behavior after an emergency has been expressed as a linear combination of the extracted factors, taking into account the weight factors obtained by the *Component Matrix* shown in Table5.

Table 5

Therefore the eight hospital variables are defined as follow:

$$a = 0.7F_1 - 0.292F_2 - 0.541F_3 \tag{3}$$

$$b = 0.877F_1 + 0.4F_2 + 0.002F_3 \tag{4}$$

$$c = 0.086F_1 + 0.637F_2 + 0.648F_3 \tag{5}$$

$$d = 0.643F_1 + 0.676F_2 - 0.146F_3 \tag{6}$$

$$e = 0.715F_1 - 0.388F_2 + 0.223F_3 \tag{7}$$

$$f = 0.259F_1 - 0.489F_2 + 0.668F_3 \tag{8}$$

$$g = 0.842F_1 + 0.255F_2 + 0.029F_3 \tag{9}$$

$$h = 0.624F_1 - 0.716F_2 + 0.094F_3 \tag{10}$$

A performance index to assess hospital resilience has been proposed combining the three factors which have different contributions on the overall resilience.

The numerical quantification of each factor has been determined using the regression analysis based on the Factor Score Coefficient Matrix given in Table 6. Table 6 shows the correlation between the factors and the coefficients used to produce the factor scores through multiplication.

Table 6

Thus, the factors are determined as linear combination of the variables using the coefficients given in Table 6.

$$F_1 = 0.142a + 0.322b + 0.135c + 0.349d + 0.056e - 0.120f + 0.273g - 0.042h \qquad (11)$$

$$F_2 = -0.063a + 0.006b + 0.122c - 0.184d + 0.331e + 0.505f + 0.059g + 0.358h \qquad (12)$$

$$F_3 = 0.479a - 0.038b - 0.579c - 0.032d + 0.010e - 0.286f - 0.021g + 0.12h \qquad (13)$$

Estimation of the resilience index

After the factors have been determined, the hospital's disaster resilience indicator (*R*) is determined as a linear combination of three factors as follow

$$R = \alpha F_1 + \beta F_2 + \chi F_3 \qquad (14)$$

where F_1, F_2, F_3 are the extracted factors, calculated using equations (11), (12) and (13); α, β, χ are the corresponding weight factors which have been calculated as ratio between the percentage of variance corresponding to each factor and the cumulative variance of the three main factors. Substituting the numerical values of the weight factors in Equation (14), the following expression for hospital disaster resilience is obtained:

$$R = 0.503F_1 + 0.311F_2 + 0.186F_3 \qquad (15)$$

The weight for *hospital cooperation and training management* is 0.503, for *hospital resource and equipment* is 0.311 and for *hospital structural and organizational operating procedures* is 0.186. This means that the first factor is more relevant to assess the resilience of healthcare facilities, representing about 50% of the hospital emergency preparedness and response.

Three levels for hospital disaster resilience have been identified. Indeed, when the questionnaire is filled out, each of the eight items shall have an overall score, obtained by summing the scores of each question (with the score “0” or “1”). Using these scores, the three extracted factors can be calculated. Knowing the factors’ value, hospital disaster resilience index can be obtained using Equation (15). The R values are in the range:

$$0 < R < 1 \tag{16}$$

where “0” represents “no resilience “and “1” means “maximum level of resilience” corresponding to the ability to absorb any damage without suffering complete failure.

If the resilience value is above 0.75, the hospital has a high level of resilience to emergencies, while if the resilience value is below 0.25, the hospital is not able to absorb adequately disastrous events and reduce the consequences from such failures before, during, and after the event (Table 7).

Table 7

While the resilience indicator given in Equation (15) gives a global description of hospital resilience, the indicators given in Equation (11), (12) and (13) correspond respectively to cooperation and training management, resources and equipment capability, structural and organizational operating procedures. These additional indicators can help understanding which parts of the hospital system requires attention in order to increase its level of resilience.

ANALYSIS OF THE NUMERICAL RESULTS

The proposed methodology has been applied to each health care of the hospital network located in the San Francisco Bay area, in order to analyze the level of resilience in the considered geographical region considered as case study. The disaster resilience score has been calculated for each hospital as listed in the Table 8. For confidentiality reasons, hospitals' names have been replaced with a number.

Table 8

The results have been plotted in the following graph representing the resilience trend of healthcare facilities in the San Francisco's Bay Area. The chart has been divided into three sections corresponding to the three levels of hospital disaster resilience (low level, moderate level, high level).

Figure 2

According to the figure, 10 hospitals, which account for about 62.5% of the sample, have an high level of resilience ($R \geq 0.75$) while 6 hospitals, representing the remaining 37.5%, are in the moderate resilience zone ($0.25 < R < 0.75$). There are no hospitals whose resilience score is under 0.25, which means that there are no healthcare facilities with an insufficient level of resilience. These results indicate that the San Francisco Bay Area's hospitals have a generally high level of resilience.

Furthermore, the scores of the three extracted factors have been calculated to identify the areas within the hospital with a lower resilience level. In fact, the central goal of this research is not only to provide a measure of the overall resilience level in the San Francisco's Bay Area, but also to identify the factors with a lower level of resilience. This analysis allows focusing on the areas that need improvement and helps finding information about the most effective strategies for improving the quality of care. The results have been standardized so the scores range from 0 to 1. The factors' values are listed in Table 9.

Table 9

The results have been plotted in Figure 3, where is shown the trend of the extracted factors (F_1, F_2, F_3) for each hospital.

Figure 3

The figure shows that the three extracted factors have a generally acceptable performance level. It can be observed that among them, factor F_2 (Resources and Equipment Capability) has the lowest performance level. Figure 3 show clearly that if some improvement wants to be made in order to increase the overall level of resilience of the hospital network, the resource and equipment capability of the network needs to be analyzed.

CONCLUDING REMARKS

Hospitals and other health facilities are vital assets to communities when a disaster strikes. Therefore the capacity of a community to respond to a disaster is affected by how long it takes for a hospital to recover in order to continue their function providing medical care. A resilient hospital is a facility that is able to govern, resist and recover after a disaster has struck. In this paper, a fast methodology to measure hospital disaster resilience has been developed. Factor analysis has been used to analyze the multivariate empirical data and a three factors solution has been obtained. The extracted factors from the analysis are the following: (i) cooperation and training management, (ii) resources and equipment capability, (iii) structural and organizational operating procedures. An analytical expression is proposed to evaluate hospital disaster resilience that linearly combines the extracted factors, while the corresponding weight factors are determined by the variance. From the analysis it appears that the cooperation and training management (F_1) factor gives more contribution to the hospital resilience indicator because it describes the capability to coordinate different emergency departments as well as emergency training programs.

The proposed methodology has been applied to the hospital network of the San Francisco Bay area. The data related to the different hospitals has been collected with a questionnaire. The analysis shows a high level of resilience for the hospitals considered in the case study.

The proposed methodology based on factor analysis provides not only a measurement of hospital's preparedness before catastrophic events, but also a measure of hospital disaster resilience, such as hospital disaster leadership and cooperation, emergency plans, emergency stockpiles and logistics management, emergency training and drills, critical care capability.

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SUPPLEMENTAL DATA

The questionnaire is available online in the ASCE Library (ascelibrary.org).

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Table 1. Correlation matrix

		a	b	c	d	e	f	g	h
Correlation	**a**	1.000	0.494	-0.374	0.321	0.550	-0.040	0.377	0.549
	b	0.494	1.000	0.356	0.813	0.471	0.000	0.764	0.301
	c	-0.374	0.356	1.000	0.304	0.120	0.000	0.102	-0.346
	d	0.321	0.813	0.304	1.000	0.000	-0.111	0.745	-0.079
	e	0.550	0.471	0.120	0.000	1.000	0.292	0.441	0.686
	f	-0.040	0.000	0.000	-0.111	0.292	1.000	0.186	0.553
	g	0.377	0.764	0.102	0.745	0.441	0.186	1.000	0.318
	h	0.549	0.301	-0.346	-0.079	0.686	0.553	0.418	1.000

Table 2. Table of communalities

Variable	Extraction
(a) Hospital safety	0.869
(b) Hospital disaster leadership and cooperation	0.929
(c) Hospital disaster plan	0.834
(d) Emergency stockpiles and logistics management	0.891
(e) Emergency Staff	0.711
(f) Emergency critical care capability	0.752
(g) Emergency training and drills	0.775
(h) Recovery and reconstruction	0.910

Table 3. Total Variance Explained

Component	Initial Eigenvalues			Extracted factors			Rotated factors		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.356	41.950	41.950	3.356	41.950	41.950	2.951	36.891	36.891
2	2.075	25.932	67.882	2.075	25.932	67.882	2.101	26.257	63.148
3	1.241	15.507	83.388	1.241	15.507	83.388	1.619	20.241	83.388
4	0.779	9.735	93.124						
5	0.308	3.851	96.975						
6	0.191	2.382	99.357						
7	0.046	0.569	99.926						
8	0.006	0.074	100.000						

Table 4. Rotated Component Matrix

	Component		
	F_1	F_2	F_3
(a) Hospital safety	0.479	0.216	**0.770**
(b) Hospital disaster leadership and cooperation	**0.947**	0.178	0.006
(c) Hospital disaster plan	0.353	0.014	**-0.842**
(d) Emergency stockpiles and logistics management	**0.919**	-0.202	-0.083
(e) Emergency Staff	0.359	**0.733**	0.211
(f) Emergency critical care capability	-0.120	**0.834**	-0.208
(g) Emergency training and drills	**0.836**	0.270	0.053
(h) Recovery and reconstruction	0.118	**0.822**	0.469

Table 5. Component Matrix

	Component		
	1	2	3
a	0.700	-0.292	-0.541
b	0.877	0.400	0.002
c	0.086	0.637	0.648
d	0.643	0.676	-0.146
e	0.715	-0.388	0.223
f	0.259	-0.489	0.668
g	0.842	0.255	0.029
h	0.624	-0.716	0.094

Table 6. Factor Score Coefficient Matrix

	Component		
	1	2	3
a	0.142	-0.063	0.479
b	0.322	0.006	-0.038
c	0.135	0.122	-0.579
d	0.349	-0.184	-0.032
e	0.056	0.331	0.010
f	-0.120	0.505	-0.286
g	0.273	0.059	-0.021
h	-0.042	0.358	0.172

Table 7. Levels of hospital disaster resilience

Low level of Resilience	Moderate level of Resilience	High level of Resilience
$R \leq 0.25$ (25%)	$0.25 < R < 0.75$ (25%-75%)	$R \geq 0.75$ (75%)

Table 8. Disaster resilience scores for the considered hospitals

Hospital	R	Hospital	R
1	0.836	9	0.871
2	0.813	10	0.681
3	0.771	11	0.787
4	0.772	12	0.607
5	0.391	13	0.739
6	0.831	14	0.663
7	0.904	15	0.892
8	0.818	16	0.581

Table 9. Extracted factors scores for the considered hospitals

Hospital	F1	F2	F3	Hospital	F1	F2	F3
1	1	0.48	1	9	1	0.57	0.93
2	0.88	0.71	0.78	10	0.78	0.56	0.71
3	1	0.52	0.85	11	0.89	0.62	0.86
4	0.55	0.62	0.93	12	0.77	0.48	0.64
5	0.67	0.29	0.57	13	0.77	0.58	0.92
6	1	0.47	0.93	14	0.66	0.53	0.72
7	0.98	0.76	0.92	15	0.89	0.71	1
8	0.99	0.48	0.94	16	0.56	0.57	0.65

FIGURE CAPTION LIST