

Factor Analysis to Evaluate Hospital Resilience

Original

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

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

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

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

48

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

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

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

64 **STATE OF ART**

65 Factor analysis is a multivariate statistical approach commonly used to investigate how many latent
66 variables underlie a set of items. Historically factor analysis has been used primarily in psychology and
67 education; however its use within the health science sector has become much more common during the
68 past two decades (Williams et al., 2010). Reducing the data to a smaller set of variables could help
69 understanding some aspects of the hospitals' behavior during an emergency. Indeed, the primary aim of
70 hospital's planners during a crisis should not be trying to create plans for ever more contingencies, since
71 contingencies are numerous, but rather to create capabilities for resilience (Stenberg, 2003). Bruneau et
72 al. (2003) define a resilient system as a system which reduces failure probabilities, limits consequences

73 from failures and decreases time to restore “normal” level of functional performance. A conceptual
74 understanding of hospital resilience is essential for an integrated approach to enhance hospital resilience
75 to cope with future disasters (Cimellaro et al., 2010, 2016).

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

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

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

91 92 **METHODOLOGY**

93 In this research, a study has been conducted on Tertiary Hospitals located in the San Francisco Bay Area
94 in California. Tertiary Hospitals are referral hospitals that provide comprehensive and multidisciplinary
95 care which requires highly specialized equipment as well as full departmentalization and facilities with
96 the service capabilities. A questionnaire with 33 questions that is shown in Appendix A has been
97 developed to collect relevant data for the hospitals' resilience analysis. The survey has been conducted

98 between April 2014 and July 2014. Among all the selected hospitals in the San Francisco's Bay Area, 16
99 complete questionnaires have been collected which represent about a 71% response rate. The location of
100 the hospitals analyzed is shown in Figure 1.

101 Figure 1

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

108 **Description of the Questionnaire**

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

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

- 117 (a) Hospital safety
- 118 (b) Hospital disaster leadership and cooperation
- 119 (c) Hospital disaster plan
- 120 (d) Emergency stockpiles and logistics management

- 121 (e) Emergency Staff
- 122 (f) Emergency critical care capability
- 123 (g) Emergency training and drills
- 124 (h) Recovery and reconstruction

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

138

139 **FACTOR ANALYSIS**

140 Factor analysis is a statistical method used to investigate whether a certain number of variables of interest
141 $Y_1, Y_2... Y_n$ are related to a smaller number of unobserved variables $F_1, F_2... F_m$ called factors. A factor is
142 a hypothetical variable that influences the score on one or more observed variables. The factor analysis's
143 first goal is to determine how many factors are necessary to include all the information available in the
144 original set of statements. Different methods exist for estimating the parameters of a factor model. In this

145 research, the *Principal Component method* has been used. It consists in an orthogonal transformation that
 146 converts a number of correlated variables into a set of factors that are linearly uncorrelated and with high
 147 variance. These factors are called principal components. Therefore, each variable can be expressed as a
 148 linear combination of a number of common factors:

$$149 \quad z_j = k_{j1}F_1 + k_{j2}F_2 + \dots + k_{jh}F_m \quad (1)$$

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

$$153 \quad \begin{aligned} F_1 &= c_{11}z_1 + c_{12}z_2 + \dots + c_{1n}z_n \\ F_2 &= c_{21}z_1 + c_{22}z_2 + \dots + c_{2n}z_n \\ &\dots \\ F_m &= c_{m1}z_1 + c_{m2}z_2 + \dots + c_{mn}z_n \end{aligned} \quad (2)$$

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

157 **Correlation analysis**

158 As aforementioned, factor analysis' goal is to obtain the factors that can represent the correlation between
 159 variables. It means that these variables have to be somehow connected each other. So, if the relationships
 160 between variables are weak, it is unlikely that common factors exist. Two tests have been used to verify
 161 the presence of significant correlations between the items. The *Kaiser-Meyer-Olkin test* (KMO) is used
 162 to check whether the sample is large enough. The sample is adequate when KMO value is greater than
 163 0.5. *Bartlett's test of sphericity* compares the observed correlation matrix to the identity matrix (a matrix
 164 of zero correlation). In particular, it checks if the correlation matrix is an identify matrix implying that all

165 of the variables are uncorrelated. In this study, the KMO value is greater than 0.5 and the Bartlett's test
166 indicates that some variables are not independent. These tests suggest that the data are suitable for a factor
167 analysis, as shown in the correlation matrix in Table 1.

168

169 Table 1

170

171 The correlation matrix shows that some variables are correlated. In fact, the absolute values outside the
172 main diagonal are often close to 1 (e.g. *b* and *d*: 0.813; *g* and *b*: 0.764). This means that these variables
173 are valuable for a factor analysis. Moreover, the table of communalities has been examined to test the
174 goodness of fit. Indeed, this table shows how much of the variance in each of the original variables is
175 explained by the extracted factors. For example in the first row of Table 2 $R^2 = 0.869$ indicates that about
176 87% of the variation in hospital safety (a) is explained by the factor model. The results in Table 2 suggest
177 that the factor analysis does the best job of explaining variation in variables (b) Hospital disaster
178 leadership and cooperation, (d) Emergency stockpiles and logistics management and (h) Recovery and
179 reconstruction.

180

181 Table 2

182

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

187 **Factor extraction**

188 The *Principal Component Method* (PCA) has been used to extract the independent factors using the
189 eigenvalues determined by the analysis. The eigenvalues indicate the variance included in each principal
190 component or factor so the sum of the eigenvalues is equal to the number of variables. The number of
191 factors has been determined considering the number of eigenvalues that exceed 1.0, according to the
192 method proposed by Kaiser (1960). In fact, lower values describe less variability than does a single
193 variable. In the case study analyzed, three factors have an eigenvalue greater than 1, as shown in Table
194 3:

195

196 Table 3

197

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

201 **Truncated component solution**

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

211

212 **Rotating the factor structure**

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

225

226 Table 4

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

230 Table 4 shows a new set of values for each of the three extracted factors. The boldface values represent
231 the larger correlations of the extracted factor versus the corresponding variable. The first factor is strictly
232 connected to three items, including *hospital disaster leadership and cooperation* (0.947), *emergency*
233 *stockpiles and logistics management* (0.919), *emergency training and drills* (0.836). Three variables are
234 also included in the second factor that is primarily a *measure of emergency staff* (0.733), *emergency*
235 *critical care capability* (0.834), *recovery and reconstruction* (0.822). The third factor contains

236 information mainly from two items, *hospital safety* (0.770) and *hospital disaster plan* (0.842). Therefore,
237 some observations have been made. In fact, it is possible to see that all the items have high factor loadings
238 on only one factor.

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

244

245 (F₁) Cooperation and Training Management

246 (F₂) Resources and Equipment Capability

247 (F₃) Structural and Organizational Operating Procedures

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

249

250 **NUMERICAL RESULTS OF FACTOR ANALYSIS**

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

254

255 Table 5

256

257 Therefore the eight hospital variables are defined as follow:

258 $a = 0.7F_1 - 0.292F_2 - 0.541F_3$ (3)

259 $b = 0.877F_1 + 0.4F_2 + 0.002F_3$ (4)

260 $c = 0.086F_1 + 0.637F_2 + 0.648F_3$ (5)

261 $d = 0.643F_1 + 0.676F_2 - 0.146F_3$ (6)

262 $e = 0.715F_1 - 0.388F_2 + 0.223F_3$ (7)

263 $f = 0.259F_1 - 0.489F_2 + 0.668F_3$ (8)

264 $g = 0.842F_1 + 0.255F_2 + 0.029F_3$ (9)

265 $h = 0.624F_1 - 0.716F_2 + 0.094F_3$ (10)

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

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

271

272 Table 6

273

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

$$276 \quad F_1 = 0.142a + 0.322b + 0.135c + 0.349d + 0.056e - 0.120f + 0.273g - 0.042h \quad (11)$$

$$277 \quad F_2 = -0.063a + 0.006b + 0.122c - 0.184d + 0.331e + 0.505f + 0.059g + 0.358h \quad (12)$$

$$278 \quad F_3 = 0.479a - 0.038b - 0.579c - 0.032d + 0.010e - 0.286f - 0.021g + 0.12h \quad (13)$$

279 **Estimation of the resilience index**

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

282

$$283 \quad R = \alpha F_1 + \beta F_2 + \chi F_3 \quad (14)$$

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

$$289 \quad R = 0.503F_1 + 0.311F_2 + 0.186F_3 \quad (15)$$

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

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

$$299 \qquad \qquad \qquad 0 < R < 1 \qquad \qquad \qquad (16)$$

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

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

305

306 Table 7

307

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

313

314 **ANALYSIS OF THE NUMERICAL RESULTS**

315 The proposed methodology has been applied to each health care of the hospital network located in the
316 San Francisco Bay area, in order to analyze the level of resilience in the considered geographical region

317 considered as case study. The disaster resilience score has been calculated for each hospital as listed in
318 the Table 8. For confidentiality reasons, hospitals' names have been replaced with a number.

319

320 Table 8

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

324 Figure 2

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

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

336

337 Table 9

338

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

341 Figure 3

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

347 **CONCLUDING REMARKS**

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

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

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

367
368

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372 and Control of Sustainable Communities during Emergencies.

373

374 **SUPPLEMENTAL DATA**

375
376 The questionnaire is available online in the ASCE Library (ascelibrary.org).

377

378 **REFERENCES**

- 379 A. James O'Malley, A. M. Z., Ron D. Hays, Kimberly A. Hepner, San Keller, Paul D. Cleary. (2005).
380 "Exploratory Factor Analyses of the CAHPS Hospital Pilot Survey Responses across and within
381 medical, surgical and obstetric services." *Health services research*, 40.
- 382 Brett Williams, A. O., Ted Brown. (2010). "Exploratory factor analysis: A five-step guide for novices."
383 *Journal of Emergency Primary health care*, 8(3).
- 384 Bruneau, M., Chang, S., Eguchi, R., Lee, G., O'Rourke, T., Reinhorn, A. M., Shinozuka, M., Tierney,
385 K., Wallace, W., and Winterfelt, D. V. (2003). "A framework to quantitatively assess and enhance
386 the seismic resilience of communities." *Earthquake Spectra*, 19(4), 733–752.
- 387 Cimellaro, G. P., Renschler, C., Reinhorn, A. M., and Arendt, L. (2016). "PEOPLES: a framework for
388 evaluating resilience." *Journal of Structural Engineering*, ASCE, DOI
389 [http://dx.doi.org/10.1061/\(ASCE\)ST.1943-541X.0001514](http://dx.doi.org/10.1061/(ASCE)ST.1943-541X.0001514).
- 390 Cimellaro, G. P., Reinhorn, A. M., and Bruneau, M. (2010). "Framework for analytical quantification of
391 disaster resilience." *Engineering Structures*, 32(11), 3639–3649.
- 392 Cimellaro, G. P., Reinhorn, A. M., and Bruneau, M. (2010b). "Seismic resilience of a hospital system."
393 *Structure and Infrastructure Engineering*, 6(1-2), 127-144.
- 394 Kaiser, H. F. (1960). "The application of electronic computers to factor analysis." *Educational and
395 Psychological Measurement*, 20, 141-151.

- 396 Li, X. H., Zhao, L. J., Ruan, K. P., Feng, Y., Xu, D. S., and Ruan, K. F. (2013). (2013). "The application
397 of factor analysis to evaluate deforming behaviors of directly compressed powders." *ELSEVIER*,
398 247, 47-54.
- 399 Marjorie A. Pett, N. R. L., John J. Sullivan. (2003). *Making sense of factor analysis - The use of factor*
400 *analysis for Instrument development in health care research*.
- 401 Stenberg, E. (2003). "Planning for resilience in hospital internal disaster." *Prehospital and Disaster*
402 *Medicine*, 18(04).
- 403 Takako Nakajima, K. K., Masashie Manabe. (2012). "Management Evaluation of Public Hospital -
404 Approach from Factor Analysis." OSIPP Discussion Paper.
- 405 Zhong S., C. M., Hou X.Y., Zang Y.L., Fitzgerald G. (2014). "Development of hospital disaster
406 resilience: conceptual framework and potential measurement." *Emergency Medicine Journal*.
407
408

409

410

Table 1. Correlation matrix

	a	b	c	d	e	f	g	h
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

411

412

413

414

415

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

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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						

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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

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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

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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

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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%)

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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

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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

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453 **FIGURE CAPTION LIST**
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455 Figure 1. Tertiary hospitals in the San Francisco's Bay Area

456 Figure 2. Overall level of resilience in the San Francisco's Bay Area

457 Figure 3. Overall level of the three extracted factors F1, F2, F3