Engineering Letters, 27:3, EL_27_3_11

Using Structural Analysis to Construct Causal Relationships of the Patient Safety Culture

Jiunn-I Shieh, Chih-Hsuan Huang, Yii-Ching Lee, and Hsin-Hung Wu

Abstract—Decision making trial and evaluation laboratory method and semantic structure analysis are the two most popular approaches to study structural analysis of critical factors or dimensions but do not have solid theoretical backgrounds to construct causal relationships among critical factors or dimensions. This study proposes a framework by using normalized mutual information for both continuous and discrete random variables to set up the contextual relationships from the raw data. A Monte Carlo simulation based on normalized mutual information is conducted to estimate the threshold value of establishing the causal relationships. Two internal survey data of safety attitudes questionnaire in terms of thirty questions and six dimensions are used from viewpoints of physicians and nurses. Four cases are illustrated to show how the proposed framework works in practice to identify critical factors or dimensions from the internal survey data. This proposed framework enables hospital management to initiate improvements from causal factors or dimensions to effectively enhance patient safety from medical staffs' viewpoints.

Index Terms—normalized mutual information, random variable, Monte Carlo simulation, safety attitudes questionnaire, patient safety culture, causal relationship

I. INTRODUCTION

Patient safety culture has become an ad hoc topic in recent years in order for hospital management to reduce medical errors and enhance patient safety and satisfaction for patients with their families in healthcare organizations [1], [2]. The safety attitudes questionnaire developed by Sexton et al. [3] has been widely used worldwide to monitor and understand the status of medical services in healthcare organizations [4,5]. To relentlessly improve the patient safety culture, identifying strengths and weaknesses in healthcare organizations are essentially important for hospital management [2]. That is, enhancing the strengths enables hospital management to maintain the competitiveness or even increase the lead among healthcare organizations in the medical industry. In contrast, improving the weaknesses helps hospital management reduce patients' dissatisfaction and medical malpractice and shorten the gap among healthcare organizations.

To effectively improve the patient safety culture relentlessly, it is critically important to understand the causal relationships among critical factors or dimensions. Shieh et al. [6] pointed out that improvements can be made based on those causal factors or dimensions first in order to reduce costs and enhance patients' satisfaction more effectively when critical factors or dimensions are identified and their causal relationships are established. In practice, decision making trial and evaluation laboratory (DEMATEL) and semantic structure analysis (SSA) are the most commonly seen methods to construct the contextual relationships [6-12]. DEMATEL method is typically used in a relatively smaller group of people or experts [13-16] based on experts' opinions. However, two major limitations are found for DEMATEL method [6]. First, the information gathered from experts is assumed to be reliable without further assessing its reliability. Second, DEMATEL method uses pairwise comparisons between a pair of factors or dimensions. To make effective and consistent evaluations by experts, the number of factors or dimensions should be limited. For instance, if there are 13 factors or dimensions, each expert will be requested to assess 78 (C_2^{13}) relations. In fact, the consistency would be in doubt.

Semantic structure analysis, on the other hand, uses a graphical relational structuring method to compare factors or dimensions based on rating scale data such that the causal relationships can be established. Compared with DEMATEL method, SSA is more flexible to help decision makers set up the relational structure among factors or dimensions from either a smaller group of experts or a larger group of respondents [6], [17]. The SSA method has the ability to address the reliability and validity of the data if a larger group of experts such as > 30 is available through data mining techniques.

There is no limitation on the number of factors or dimensions for the SSA method. For instance, if there are 13 factors or dimensions, each person is requested to evaluate 13 questions. The relational structure among factors or dimensions can be established by computing the ordering coefficients and the threshold value [8], [17]. However, if a smaller group of experts is less than 30, the SSA method is lack of the ability to assess the reliability and validity of the data. More importantly, the reason why threshold value of 0.93 is recommended by Takeya [17] cannot be understood without further explanation.

Previous studies conducted by Lee et al. [18] and Lee et al. [19] used dimensions of the safety attitudes questionnaire and

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Manuscript received January 3, 2019; revised May 21, 2019. This study was partially supported by Ministry of Science and Technology in Taiwan with the grant number of MOST 106-2221-E-468 -008 -MY2.

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the Chinese version of the safety attitudes questionnaire, respectively, to establish causal relationships among dimensions from a group of experts to identify critical dimensions of the patient safety culture. Lee et al. [20] further re-assessed the causal relationships among dimensions of the safety attitudes questionnaire in 2018. In their studies, the information gathered from experts was assumed to be valid without further assessing its reliability. Their studies provide an overall viewpoint for hospital management to understand the causal relationships among dimensions. However, different healthcare organizations might have different organizational culture and the contextual relationships might vary from hospital to hospital or even from country to country. Moreover, different experts might have different ratings or opinions on dimensions in terms of the causal relationship. Thus, the better approach is to establish the contextual relationship for each healthcare organization by listening to its medical staffs' voices. That is, a custom-made causal relationship for each healthcare organization can be developed through its internal survey data.

In Taiwan, each healthcare organization conducts the patient safety culture assessment annually based on the safety attitudes questionnaire developed by Sexton et al. [3] from medical staffs' viewpoints. In order to provide a custom-made causal relationship for a particular healthcare organization, the annual internal data from the safety attitudes questionnaire can be used for analyses to figure out medical staffs' attitudes toward patient safety. In practice, each healthcare organization might consist of hundreds of medical staffs. Thus, DEMATEL method is not suitable to establish the contextual relationships among dimensions from a very large group of people. On the other hand, the SSA method using the predetermined threshold value of 0.93 to establish the causal relationships without further explanations might be in doubt. That is, both methods do not have solid theoretical backgrounds to construct causal relationships among factors or dimensions as well as the threshold values [6]. In this study, normalized mutual information is employed to study causal relationships among critical factors or dimensions and, later, a Monte Carlo simulation is used to estimate the threshold value based on raw data to overcome the above drawbacks.

This paper is organized as follows: Section 2 briefly reviews entropy, mutual information, conditional entropy, normalized mutual information, Monte Carlo simulation, and the safety attitudes questionnaire. A proposed framework based on normalized mutual information and Monte Carlo simulation is depicted in Section 3. An example of applying normalized mutual information and Monte Carlo simulation to establish the relation structures among the factors and dimensions is conducted and described in Section 4. Finally, conclusions are drawn in Section 5.

II. LITERATURE REVIEW

A. Entropy

Shannon [21] introduced the concept of entropy to measure the uncertainty of a random variable. For a user's interest, a random variable with large entropy is more important than a random variable with small entropy [22]. Entropy, one of the weighting approaches, can be applied in either ordinal or metric data without the underlying assumption that data are to be normally or symmetric distributed [23]. Entropy can also be applied in nominal data. Let X be a discrete random variable and P^X be the probability of X, then the entropy of X is defined as follows:

$$H(X) = -\sum P^X \log_2 P^X \ , \tag{1}$$

Note that entropy is computed in Equation (1) for those states with the positive probabilities. For convenience, $-0 * \log_2(0)$ is set to zero. When the relationship between two different items in the questionnaire is known and to be non-linear, the philosophy of mutual information is introduced.

B. Mutual Information

Mutual information is a good measure of stochastic dependence. A higher mutual information value shows a result of a stronger association, whereas a mutual information value of zero indicates the variables are independent [24], [25]. Let X and Y be discrete random variables, the definition of mutual information between X and Y can be defined as follows:

$$MI(X, Y) = H(X) + H(Y) - H(X,Y), \tag{2}$$

where $H(X)$ is the entropy of X, $H(Y)$ is the entropy of Y, and $H(X, Y)$ is the joint entropy of X and Y [26]. The joint entropy of X and Y is defined by the following equation [25], [26]:

$$H(X, Y) = -\sum_{x,y} P(x,y) \log_2 P(x,y), \tag{3}$$

where $P(x, y)$ is the joint probability of each pair of possible outcomes (x, y).

Mutual information defined by Equation (2) provides a well-defined and complete measure of associations yielding the values in the range of $[0,\infty)$, which is unfamiliar and has no obvious interpretation. Note that $MI(X, Y) \leqq H(X)$ and $MI(X, Y) \leqq H(Y)$ [26]. Therefore, we can normalize $MI(X, Y)$ by $H(X)$ or $H(Y)$. For a clear interpretation, the conditional entropy into mutual information is introduced.

C. Conditional Entropy

Arndt [27] introduced the conditional entropy to quantify the remaining entropy (i.e. uncertainty) of a random variable Y given that the value of another random variable X is known. The entropy of Y conditional on X is denoted as $H(Y \mid X)$. The entropy $H(Y)$ is to measure the uncertainty in a realization of Y, whereas $H(Y \mid X)$ is to quantify how much uncertainty the realization of a random variable Y has if the outcome of another random variable X is known [26].

The conditional entropy is defined as

$$H(Y \mid X) = -\sum \left(P(x,y) \log_2 \frac{P(x,y)}{P(x)} \right). \tag{4}$$

Therefore, $MI(X, Y)$ can be rewritten as $H(X)-H(X\mid Y)$ or $H(Y)-H(Y\mid X)$ by using Equation (4) [26].

D. Normalized Mutual Information for Discrete Random Variables

For an obvious interpretation, Coombs et al. [28] defined a normalized mutual information by the following equation:

$$I_{y,x}=1-\frac{H(Y\mid X)}{H(Y)}=\frac{MI(Y,X)}{H(Y)}. \tag{5}$$

From the fact that $H(Y\mid X)\leq H(Y)$, $I_{y,x}$ ranges from zero to one. That is, $I_{y,x}=0$ if and only if these two variables are independent, and $I_{y,x}=1$ if and only if these two variables are functionally related in either linearly or non-linearly. Moreover, the index is applicable to both non-metric and metric data. Note that $H(Y)=M(Y,Y)$.

E. Normalized Mutual Information for Continuous Random Variables

A more accurate way to approximate the continuous probability density function is the kernel method. The kernel-based mutual information is to measure the degree of independence of two continuous random variables based on a kernel density estimate of the mutual information between a discretized approximation of the continuous random variables.

For continuous variables, a computationally efficient Gaussian Kernel estimator can be used to estimate mutual information [29]. Given a set of two-dimensional measurements, $\vec{z}_i=\{x_i,y_i\}$, i = 1, 2, …, m, the joint probability density is approximated as $f(\vec{z})=(1/m)\cdot\sum_i h^{-2}G\left(h^{-1}\left|\vec{z}-\vec{z}_i\right|\right)$, where $G(\ldots)$ is the bivariate standard normal density and $h=\left(4/3\right)^{\frac{1}{5}}\cdot n^{-\frac{1}{5}}$ and n is the sample of size [30]. Let $f(x)$ and $f(y)$ be the marginals of $f(\vec{z})$, then the mutual information is computed below [31]:

$$MI(\{x_i\},\{y_i\})=\frac{1}{m}\sum_i \log\frac{f(x_i,y_i)}{f(x_i)\cdot f(y_i)}. \tag{6}$$

The same as the discrete random variable case, $H(\{y_i\})$ can be calculated from $MI(\{y_i\},\{y_i\})$ by the following equation:

$$H(\{y_i\})=MI(\{y_i\},\{y_i\}). \tag{7}$$

Then the normalized mutual information for continuous random variables can be computed as follows:

$$I_{y,x}=\frac{MI(\{y_i\},\{x_i\})}{MI(\{y_i\},\{y_i\})}. \tag{8}$$

It is well known that mutual information is reparameterization invariant [32]. For mutual information estimation, take the copula-transform (i.e., rank-order) of x and y. After the copula-transform, the range of these new variables is between 0 and 1. Their marginal probability distributions are also more uniform [33]. The advantage of the copula transform is to make each transformed marginal variable having a uniform probability distribution. This can decrease the influence of any transformation involving in data preprocessing and remove the need to deal with position-dependent kernel widths, h, when non-uniformly distributed data are used.

F. Monte Carlo Simulation

Jon von Neumann and S. M. Ulam in the 1940's were first to use the idea of Monte Carlo simulation [34-37]. It is needed to know the distribution of the population in inferential statistics. Monte Carlo simulation was introduced to deal with the cases in inferential statistics when the information of the distribution of the population is not available by an easy and inexpensive approach to understand the population or phenomena of interest [38]. To conduct a Monte Carlo simulation, a model that can represent the population or phenomena of interest is needed. Besides, the data generated from the repeated random sampling from the model can then be studied as if they were observations.

Martinez and Martinez [39] summarized the procedure of a Monte Carlo hypothesis testing as below: (1) Use an available random sample of size n from the population of interest. Then, compute the observed value of the test statistic, t_0. (2) Decide on a pseudo-population that reflects the characteristics of the true population under the null hypothesis, H_0. (3) Repeatedly draw random samples of size n for M trials from the pseudo-population and observe the behavior of the statistic over the samples. That is, estimate the distribution of the statistic from the pseudo-population and record it for each sample. Assume that there are M values, namely t_1, t_2, …, and t_M that serve as an estimate of the probability distribution of the test statistic, T, when H_0 is true. (4) Obtain the critical value for the given significance level α. In general, there are three cases to obtain the critical value: low tail test, upper tail test, and two-tail test. The descriptions are as follows: (a) low tail test, obtain the α-th sample quantile, $\hat{q}_\alpha$, from the values of M trials in Step 3. If t_0 is less than $\hat{q}_\alpha$, then t_0 falls in the rejection region; (b) upper tail test, obtain the (1-α)-th sample quantile, $\hat{q}_{1-\alpha}$, from the values of M trials. If t_0 is greater than $\hat{q}_\alpha$, then t_0 falls in the rejection region; (c) two-tail test, obtain the sample quantiles $\hat{q}_{\alpha/2}$ and $\hat{q}_{1-\alpha/2}$ from the values in Step 3. If t_0 is greater than $\hat{q}_{\alpha/2}$ or less than $\hat{q}_{1-\alpha/2}$, then t_0 falls in the rejection region. (5) If t_0 falls in the rejection region, then reject H_0.

G. Safety Attitudes Questionnaire

Patient safety culture has become one of the most essential ways to improve the medical services in healthcare organizations [2], [40], [41]. Johari et al. [42], Leufer and Cleary-Holdforth [43], and Lee et al. [5] concluded that a positive patient safety culture has been proven to result in several benefits for healthcare organization. For instance, Johari et al. [42] pointed out that medical staffs with a better attitude toward patient safety could reduce medical errors and increase patient satisfaction. Lee et al. [5] stated that healthcare organizations could lower adverse events such as patient falls, medical errors, and work absence by emphasizing the patient safety culture. That is, it is critically important for healthcare organizations to regularly assessing the frontline staffs' attitudes toward patient safety.

TABLE I
THE SAFETY ATTITUDES QUESTIONNAIRE

Dimension	Item
Teamwork Climate	1. Nurse input is well received in this clinical area. 2. In this clinical area, it is difficult to speak up if I perceive a problem with patient care. 3. Disagreements in this clinical area are resolved appropriately (i.e., not who is right, but what is best for the patient). 4. I have the support I need from other personnel to care for patients. 5. It is easy for personnel here to ask questions when there is something that they do not understand. 6. The physicians and nurses here work together as a well-coordinated team.
Safety Climate	7. I would feel safe being treated here as a patient. 8. Medical errors are handled appropriately in this clinical area. 9. I know the proper channels to direct questions regarding patient safety in this clinical area. 10. I receive appropriate feedback about my performance. 11. In this clinical area, it is difficult to discuss errors. 12. I am encouraged by my colleagues to report any patient safety concerns I may have. 13. The culture in this clinical area makes it easy to learn from the errors of others.
Job Satisfaction	14. I like my job. 15. Working here is like being part of a large family. 16. This is a good place to work. 17. I am proud to work in this clinical area. 18. Morale in this clinical area is high.
Stress Recognition	19. When my workload becomes excessive, my performance is impaired. 20. I am less effective at work when fatigued. 21. I am more likely to make errors in tense or hostile situations. 22. Fatigue impairs my performance during emergency situations (e.g. emergency resuscitation, seizure).
Perceptions of Management	23. Management supports my daily efforts. 24. Management doesn't knowingly compromise patient safety. 25. I get adequate, timely information about events that might affect my work. 26. The levels of staffing in this clinical area are sufficient to handle the number of patients.
Working Conditions	27. Problem personnel are dealt with constructively by our unit. 28. This hospital does a good job of training new personnel. 29. All the necessary information for diagnostic and therapeutic decisions is routinely available to me. 30. Trainees in my discipline are adequately supervised.

The safety attitudes questionnaire developed by Sexton et al. [3] has been widely used worldwide to assess the perceptions of patient safety in healthcare organizations from medical staffs' viewpoints [44], [45]. There are six dimensions along with 30 questions in the safety attitudes questionnaire. The detailed information of the safety attitudes questionnaire is summarized in Table I. Six dimensions are teamwork climate (perceived quality of collaboration between personnel), safety climate (the perceptions of a strong and proactive organizational commitment to safety), job satisfaction (the positivity about the work experience), stress recognition (the measurement on how performance is influenced by stressors), perception of management (the approval of managerial actions), and working conditions (the perceived quality of the work environment and logistical support such as staffing and equipment) [2].

Each question uses a five-point Likert's scale ranging from strongly agree to strongly disagree. In addition, there are two reversed questions. Thus, each respondent's answer needs to be adjusted. The score for each dimension is to average the scores of questions under that particular dimension. Then, there are six continuous random variables. Therefore, the normalized mutual information for continuous random variables is employed in this study.

III. A PROPOSED FRAMEWORK BASED ON NORMALIZED MUTUAL INFORMATION AND MONTE CARLO SIMULATION

The proposed framework consists of three major step depicted below:

Step 1: Construct the ordering network. A pair of items could be linked if the level of observed ordering relationship exceeds the significance level. To compute the normalized mutual information, data with discrete random variables and continuous random variables are used respectively.

The normalized mutual information $I_{i,j}$ for discrete random variables between item *i* and item *j* is as follows:

$$I_{i,j} = 1 - \frac{H(X_i \mid X_j)}{H(X_i)}, \tag{9}$$

where $H(X_i \mid X_j)$ is the conditional entropy of *i*-th item for given *j*-th item. To simplify the computation, Equation (9) can be expressed as follows:

$$I_{i,j} = \frac{MI(X_i, X_j)}{H(X_i)} = \frac{H(X_i) + H(X_j) - H(X_i, X_j)}{H(X_i)}. \tag{10}$$

To calculate $I_{i,j}$ for given item *i* and item *j* from the survey data where a five-point (level) Likert's scale is applied to X_i and X_j, first calculate $P(X_i = a)$ for each item *i* with *a* = 1, 2, 3, 4, and 5. Let n_a be the number of the level *a* for X_i, and *N* be the total number of questionnaire, then $P(X_i = a)$ = n_a /*N*. Second, calculate $P(X_j = c)$ with *c* = 1, 2, 3, 4, and 5. Let n_c be the number of the level *c* for the item X_j, then $P(X_j = c)$ = n_c /*N*. Third, compute $P(X_i = a, X_j = c)$ for all levels *a* and *c*. Let $n_{ac}(i, j)$ be the number of the level *a* for item X_i and the level *c* for item X_j, then

$P(X_i = a, X_j = c) = n_{ac}(i,j) / N$. Repeat the process to calculate $P(X_i = a, X_j = c)$ for the other items. Finally, calculate $H(X_i)$ by Equation (1) and $MI(X_i, X_j)$ by the formula of $H(X_i) + H(X_j) - H(X_i, X_j) = (-\sum P(X_i = a) \log_2 P(X_i = a)) + (-\sum P(X_j = c) \log_2 P(X_j = c)) - (-\sum P(X_i = a, X_j = c) \log_2 P(X_i = a, X_j = c))$. Next, calculate the normalized mutual information by the formula of $MI(X_i, X_j) / H(X_i)$.

For the normalized mutual information $I_{i,j}$ for continuous random variables, first use copula-transform (i.e., rank-order) of x and y to compute mutual information estimation [33]. Then, the range of these transformed variables is between 0 and 1. Next, use Equations (6) and (7) to calculate normalized mutual information by Equation (8).

Step 2: Determine if the $I_{i,j}$ is significant. The normalized mutual information threshold can be obtained by using Monte Carlo simulation based on the raw data. The procedure is as follows: (i) randomly select any pair of items from all items in the questionnaire; (ii) compute the normalized mutual information $I_{i,j}$; (iii) repeat Steps (i) and (ii) for 10,000 times to obtain a distribution of the normalized mutual information $I_{i,j}$ and determine the normalized mutual information threshold $I_{i,j}$ at the significant levels of 0.05.

Step 3: The edge $j \rightarrow i$ would be created if the normalized mutual information $I_{i,j}$ between the pair of items i and j exceeds the threshold. Therefore, the ordering networks can be constructed as directional graphs.

IV. CONSTRUCTING THE CAUSAL RELATIONSHIPS BASED ON INTERNAL SURVEY DATA

Two surveys using the safety attitudes questionnaire with 30 questions by a five-point Likert's scale were conducted from viewpoints of physicians and nurses of a regional teaching hospital in Taichung City, Taiwan. The first survey conducted in November 2015 has a sample size of 376, whereas the second survey conducted in November 2016 has a sample size of 432. Coefficient alpha is used to measure the degree of reliability, and the overall reliabilities are 0.9571 and 0.9509 for the first and second respective survey results, which are well above the usual recommendation of $\alpha = 0.7$ [46], [47]. The structures in factor analysis performed well by Kaiser-Meyer-Olkin statistic of 0.9569 and 0.9579 for the first and second survey results, respectively. The p-values of both questionnaires are also less than 0.001, respectively, indicating the questionnaire has a good construct validity. In this study, the causal relationships of the patient safety culture using the safety attitudes questionnaire will be established based on 376 and 432 respondents' opinions by six dimensions along with 30 questions in both 2015 and 2016.

To follow the procedures developed in Section 3, the first step is to construct the ordering networks. In this study, there are four ordering networks to be constructed, i.e., (A) an ordering network with 30 questions using the data in 2015; (B) an ordering network with six dimensions using the data in 2015; (C) an ordering network with 30 questions using the data in 2016; and (D) an ordering network with six dimensions using the data in 2016. The normalized mutual information can be computed by Equation (10) for discrete random variables (that is, cases (A) and (C) in our study). For cases (B) and (D), the normalized mutual information can be computed by Equation (8). For instance, if $I_{1,2}$ is to be computed in accordance with Equation (10), N (the total number of questionnaire) is set to 376 for the cases (A) and (B) and 432 for the cases (C) and (D), and the possible values of a and c are 1, 2, 3, 4, or 5 when a 5-point Likert's scale is used for cases (A) and (C), whereas the kernel-based mutual information is used in accordance with Equation (8) when a dimensional scale is used for cases (B) and (D).

Step 2 is to calculate the normalized mutual information threshold I_{th} for cases (A), (B), (C), and (D). The procedure is first to obtain any pair of items from 30 questions in case (A), calculate the value of the test statistic using the random sample in Step 1 and record it, and repeat the steps for 10,000 trials to generate the values of t_1, t_2, …, and $t_{10,000}$. Finally, obtain the critical values for the given significance level of 0.05, i.e., $\alpha = 0.05$, for upper tail test with the (1-α)-th sample quantile from the values. Repeat the above process for case (B) with six dimensions. Also, repeat the above process for case (C) with 30 items as well as for case (D) with six dimensions.

In Step 3, compute the normalized mutual information $I_{i,j}$ between items i and j with the threshold I_{th} at the significant level of 0.05 for Cases (A), (B), (C), and (D), where the respective values are 0.3363, 0.7088, 0.3318, and 0.6275. If the value of $I_{i,j}$ in each case is greater than the correspondent threshold, then the edge would be created. Therefore, the digraphs of Cases (A), (B), (C), and (D) are depicted in Fig. 1, 2, 3, and 4, respectively, with the significant level of 0.05. In Cases (A) and (C), the numerical figures from 1 to 30 represent the numbers of the questions in the safety attitudes questionnaire, while the numerical figures from 1 to 6 are the dimensions representing teamwork climate, safety climate, job satisfaction, stress recognition, perceptions of management, and working conditions, respectively, in Cases (B) and (D). The specific effects of Cases (A) and (C) depicted in Fig. 1 and 3 are summarized in Table II.

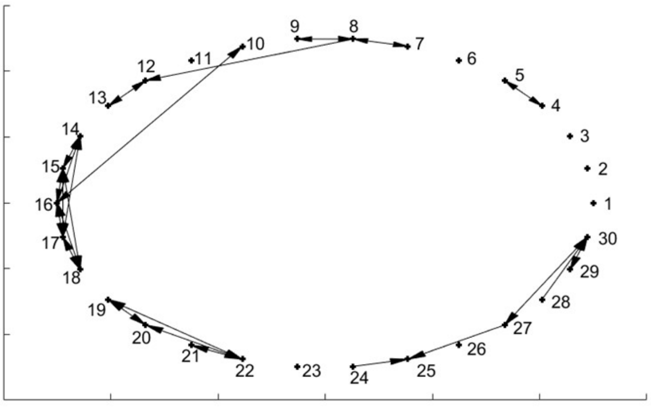

Fig. 1. The digraph of 30 questions from 2015 data with α = 0.05 in Case (A).

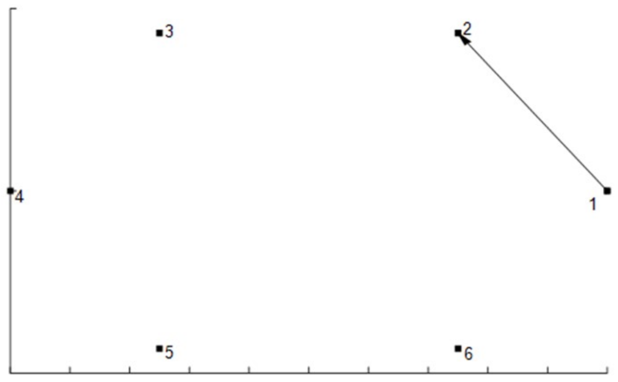

Fig. 2. The digraph of 6 dimensions from 2015 data with $\alpha = 0.05$ in Case (B).

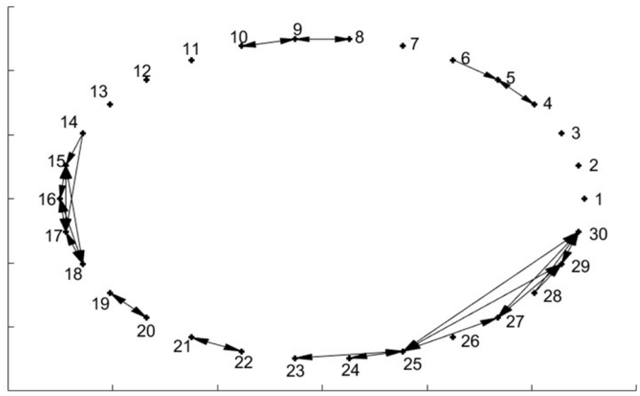

Fig. 3. The digraph of 30 questions from 2016 data with $\alpha = 0.05$ in Case (C).

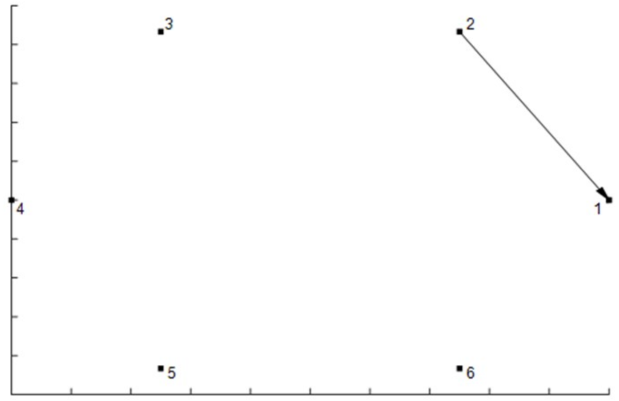

Fig. 4. The digraph of 6 dimensions from 2016 data with $\alpha = 0.05$ in Case (D).

For hospital management, the causal relationships among six dimensions can be observed as well as those among thirty questions. For instance, teamwork climate has the influence on safety climate in 2015. That is, an improvement on teamwork climate would result in a positive impact on safety climate. On the contrary, safety climate has an impact on teamwork climate in 2016. Thus, an improvement on safety climate would enhance teamwork climate. Echoing the study conducted by Pinheiro and Uva [48], our findings also state that the more teamwork is exhibited among medical staffs, the more safety of patients is committed. Finally, the contextual relationships among thirty questions in 2015 and 2016 are quite complicated. It is interesting to note that question items 14, 15, 16, 17, and 18 in both 2015 and 2016 are mutually influenced. That is, items in job satisfaction dimension have causal relationships among any pair questions in general. Obviously, hospital management can enhance both physicians' and nurses' job satisfaction through improving one of the items in job satisfaction dimension based on the causal relationship viewpoints. Because of the complicated relationships among thirty questions as shown in Fig. 1 and 3, hospital management might adjust different α values such as $\alpha = 0.01$ or even smaller to reduce the complexity of causal relationships for better understanding the relationships. In fact, a smaller α value can simplify the complexity of the contextual relationships among thirty questions of the safety attitudes questionnaire.

TABLE II
CAUSAL RELATIONSHIPS AMONG THIRTY QUESTIONS OF CASES (A) AND (C)

Year of Data	Causal Relationship
2015	4→5, 5→4, 7→8, 8→7, 8→9, 8→12, 9→8, 10→16, 12→13, 13→12, 14→15, 14→17, 15→14, 15→16, 15→17, 15→18, 16→10, 16→14, 16→15, 16→17, 16→18, 17→14, 17→15, 17→16, 17→18, 18→15, 18→16, 18→17, 19→20, 19→22, 20→19, 20→22, 21→22, 22→19, 22→20, 22→21, 24→25, 27→25, 27→30, 28→30, 29→30, 30→27, and 30→29.
2016	4→5, 5→4, 6→5, 8→9, 9→8, 9→10, 10→9, 14→15, 14→17, 15→16, 15→17, 15→18, 16→15, 16→17, 16→18, 17→15, 17→16, 17→18, 18→15, 18→16, 18→17, 19→20, 20→19, 21→22, 22→21, 23→25, 24→25, 25→23, 25→24, 25→27, 25→29, 25→30, 27→25, 27→29, 27→30, 28→29, 28→30, 29→25, 29→27, 29→30, 30→25, 30→27, and 30→29.

V. CONCLUSIONS

Understanding the contextual relationships among critical factors or dimensions of the patient safety culture is critically important for hospital management to enhance patient safety and patient's satisfaction more effectively. Unlike decision making trial and evaluation laboratory and semantic structure analysis that do not have solid theoretical backgrounds to construct causal relationships among factors or dimensions as well as the threshold values, this study uses a normalized mutual information to study causal relationships among critical factors or dimensions and a Monte Carlo simulation to estimate the threshold value based on raw data to overcome the above drawbacks. A framework based on a normalized mutual information and a Monte Carlo simulation is proposed with three major steps. In addition, the proposed framework has solid theoretical backgrounds to set up the causal relationships as well as to estimate the threshold values and is suitable for both discrete and continuous random variables.

Four cases are illustrated from the internal survey data of the safety attitudes questionnaire developed by Sexton et al. [3] of a regional teaching hospital in Taiwan in 2015 and 2016 from the viewpoints of physicians and nurses to construct the causal relationships in terms of thirty questions and six dimensions. Items in job satisfaction dimension in both 2015 and 2016 are mutually influenced positively. That is, any improvement on a particular item would significantly enhance the other item in order to increase physicians' and nurses' job satisfaction. Besides, teamwork climate affects safety climate in 2015, while safety climate influences teamwork climate in 2016. Obviously, these two dimensions might influence each other. An improvement on teamwork climate (safety climate) would result in better safety climate (teamwork climate). With the proposed framework, hospital management can initiate any improvement from causal factors or dimensions to enhance patient safety more effectively.

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