On Measuring the Criticality of Various Variables and Processes in Organization Information Systems: Proposed Methodological Procedure

Jagdish PATHAK[1], Abdulkadir HUSSEIN[2], Ram SRIRAM[3], S. Ejaz AHMED[2]
[1]Odette School of Business, University of Windsor, Canada
[2]Math & Statistics Dept., University of Windsor, Canada
[3]Robinson School of Business, Georgia State University, Atlanta, USA
jagdish@uwindsor.ca ahussein@uwindsor.ca accrss@langate.gsu.edu seahmed@uwindsor.ca

This paper proposes methodological procedures to be used by the accounting, organizational and managerial researchers and executives to ascertain the criticality of the variables and the processes in the measurement of management control system. We have restricted the validation of proposed methods to the extraction of critical success factors (CSF) in this study. We have also provided a numerical illustration and tested our methodological procedures using a dataset of an empirical study conducted for the purpose of ascertaining the CSFs. The proposed methods can be used by the researchers in accounting, organizational information systems, economics, and business and also in other relevant disciplines of organizational sciences. The main contribution of this paper is the extension of Rockart's work [33] on critical success factors. We have extended the theory of CSF beyond the initially suggested domain of information into management control system decision making. The methodological procedures developed by us are expected to enrich the literature of analytical and empirical studies in accounting and organizational areas where it can prove helpful in understanding the criticality of individual variables, processes, methods or success factors.

Keywords: *Success Factors, Criticality Analysis, Perceptual Criticality, Critical Success Factors*

1 On Measuring the Criticality of Various Variables and Processes in Organization Information Systems: Proposed Methodological Procedure

Information systems such as, Accounting Information Systems (AIS), collect data and maintain relevant information that an organization can use to plan, manage, and evaluate its performance. Over the last few decades, the AIS have transitioned from their traditional accounting role – informing managers and others about transactions that took place in the past to influencers of the future. This because, with greater information technology support, AIS now able to collect, analyze, and report on such critical issues as strategy formulation, productivity, financial planning, outsourcing and insourcing. Because the information collected and analyzed by an AIS are so important, the reliability of AIS also becomes a very important issue [39].

Information systems, in general, are complicated systems that function through interconnected resources, objectives, perceptions and outcomes [19] [20]. To evaluate the reliability of such a complex system, we must identify the critical components of the system that contribute to the system's reliability. To evaluate the effective performance of the various components towards fulfilling the reliability of the system, we must, in turn, identify the critical factors that affect the components [41]. In the past, most studies on information system reliability approached the reliability issue as a technical review of system capacity and assessed efficiency by measuring input, process, and output related factors [1]. The review focused on such items as data errors, control procedures, and detection of target error classes in the accounts [25]. While such reviews served a useful purpose, they nevertheless ignored the critical success factors that contribute to other performance-related attributes of an information system [35] [38].

The concept of Critical Success Factors (CSF) is intuitively appealing because it focuses attention on important organizational issues as opposed to focusing only on a few technical or technology-related items. The CSF methodology is a top-down methodology that not only identifies critical success factors but that also simultaneously identifies the key information attributes a decision maker must focus on [7] [9] [32]. In this sense, CSF is an information resource approach to managing information systems rather than an information function approach that only deals only with technical review. Although CSF is a managerial and organizational approach to understanding information systems, the benefit of CSF methodology is that it requires managers to steer away from being operations managers and become information risk managers.

The benefit of identifying and managing CSFs is that it demands the manager to focus on major issues or concerns that an organization faces. At the same time identifying and understanding the CSFs is simple and they can be easily communicated to others within the organization. In the long run, working on CSFs would help the managers in controlling the factors that would contribute to information system and organizational successes.

A number of studies have examined CSF in the context of specific industries. For example, some studies examined the CSFs that are relevant to a specific industry [9]. Other studies applied the CSF concept to specific information system reliability factors such as planning, communications, and strategy [6] [11] [14]. A few other studies pointed out to the weaknesses in CSF measures [24]. These studies showed the weaknesses observed in CSF measures were the results of "a lack of adequate conceptual foundation that would facilitate measurement development and the absence of a rigorous program of measurement validation" [24].

This paper presents a measurement framework that would not only identify critical success factors but also the relative criticality of the factors identified. The paper presents an analytical procedure that computes the criticality of variables, procedures, and processes. The analytical procedure proposes a measurement procedure that permits weighting the perceived criticality of each success factor and ranking them in the order of priority. We believe that the paper would contribute to the strengthening the theoretical underpinning of CSFs and also provide a practical tool to evaluate the CSFs that were identified during an assessment of organizational information systems. The measurement framework is proposed in the context of a B2B e-commerce audit and considers the critical factors that would help an auditor in performing an e-commerce audit successfully.

2 The critical success factors approach

The concept of 'Success Factors (SF)' was initially developed by Daniel [10]. Rockart [33] refined the definition further and demonstrated the importance of critical success factors when evaluating the performance of an information system. Rockart emphasized that critical success factors are the most important attributes that a manager must identify and understand when working towards organizational objectives. He indicated that focusing on CSF is important because it points to "where things must go right." In a similar vein, [6] also defined CSF as, "few things that must go well to ensure success for a manager or an organization." Rockart [33] proposed four basic types of CSFs viz., industry CSFs, strategy CSFs, environmental CSFs, and temporal CSFs. Rockart found that the ones that are measured get done more often than those that are not measured. Consequently, Rockart suggested that each CSF to be measured and that it be associated with a specific target. Later studies used the Rockart's CSF theoretical framework to identify other factors that influenced information system performance [3] [8] [21]. These studies pointed out that, factors such as top management commitment to the use of performance information, decision-making authority, and training in performance measurement techniques to significantly influence information system development and use. The studies also highlighted technical issues such as information system problems and difficulties in selecting and interpreting appropriate performance metrics in hard-to-measure activities to play an important role in system implementation and use.

Although Rockart's study encouraged other researchers to further investigate the relevance of critical success factors for guiding organizational management, the Rockart's study itself had certain limitations. Rockart's definition of CSFs was qualitative and intuitive rather than quantitative. Rockart did not explain how he computed the SFs and how SFs were later converted into CSFs. This failure to differentiate between CSFs and SFs confounded the results of many other studies that used the Rockart's theoretical framework [26] [13] [31] [36]. These studies, most of which used Principal Component Analysis (PCA) to identify CSF, did not consider the criticality of the factors that they identified as success factors [40].

The advantage of using PCA, a mathematical procedure that transforms a number of inter-related variables into a parsimonious set of variables, is relatively easy to compute and understand. The first PC or Principal Component accounts for as much of the variance as mathematically possible, while succeeding components account for as much of the remaining variances as possible. The PCA methodology is very useful for analyzing collinear data, where multiple variables could be co-related. The multicollinearity, even when present, does not confound the results. While PCA, as a methodology, has several advantages, the limitation of prior studies was that they used the PCA methodology without elaborating on the method/procedure used to assign criticality.

Although, collectively, the prior studies contributed to the development of CSF as an information system evaluation methodology, the studies were limited in their contributions because of the ad-hoc approach they took to formalize critical performance measures [12]. As pointed out, most of these studies used subjective approaches to formalize the critical measures [17]. Additionally, in many cases, the researchers used intuition and personal experiences to weigh the critical factors and this weakened the validity of the results even further [35]. As [22] point out, there were several limitations and inconsistencies including, econometric problems in the application of CSF methodologies.

Given the limitations of CSF methodologies, we propose a CSF methodology that would be less subjective than some of the prior CSF methodologies. We believe that our proposed methodology would help information system managers in identifying the critical success factors and in quantifying the criticality of the variables that they have identified. Therefore, we propose a measurement procedure that correlates the relationship between a critical factor and its contribution to organizational success. We believe that our methodology could be applied to any empirical study that examines perceptions, outcomes of respondents or processes in the context of criticality. Since the methodology is not issue-specific or industry-specific, the methodology could be applied across industries of different dimensions and technological or organizational sophistications. Since CSF theory is widely used in such diverse disciplines as auditing, accounting, finance, and marketing sciences, we also believe that the methodology would be found useful by researchers from multiple disciplines.

The specific objectives of this paper are: (1) propose measurement procedures that would compute CSFs from amongst SFs (we will use the PCA for this purpose); (2) test and validate the proposed procedures using a numerical illustration; and (3) validate the results further by using a hypothetical and empirical datasets.

3 Methodology

The methodology we propose is based on the following factors: 1) that responses from individuals will be available that identifies critical success factors and factors that are not critical related to a managerial/technological issue; 2) that we can independently measure the subjectively-determined critical variables obtained from the respondents; and 3) that by using PCA, we can assign weights and use the weights to differentiate between critical and non-critical attributes. The methodology is developed on the assumption that a researcher can obtain perceptual (or subjective) responses from respondents on critical and non-critical factors. Such responses can be collected either by conducting an experiment or through a survey instrument.

The responses (either in an experiment or a survey instrument) can be required on a two separate five point Likert scale instruments. The first Likert scale instrument would provide responses on whether an item or attribute is a success factor and the second Likert scale instrument would show whether the success factor that was identified by the respondents is also a critical factor. The responses from the first Likert instrument would be analyzed using PCA to understand the importance of each success factor (based on their relative variances). Later, we will apply the methodology that we have developed to the success factors identified from the first stage analysis to understand the criticality of each success factors. The analysis will be performed in two stages. The first stage is a direct method; that is, the methodology would be applied to PCA weights (loadings) obtained from the original PCA that identified the success factors. The second stage is an indirect method and requires that the investigator assign weights to the original observations (or variables) in the study and then apply the PCA to the weighted variables. Therefore, in the first stage, the success factors are identified by a subjective approach while, in the second stage, the criticality of each success factor is determined using a pre-weighted variables. While, the second approach also involves a certain amount of subjectivity, unlike in the first approach, the pre-weights can be modified to suit organizational and technological objectives and strategies. The steps are further elaborated on the following paragraphs.

Suppose we have p correlated variables measuring certain characteristics or judgments of individual attributes in a population. These variables could either be measured on a Likert scale (1-5) or they could be continuous variables. The p variables would form a p-dimensional vector, $x = (x_1, ..., x_p)'$ with a covariance matrix Σ. From here on, when applying PCA, we will use the population-based covariance matrix Σ instead of the sample covariance matrix. The principal components or PCs of the p-dimensional population are defined as the uncorrelated p variables $y_1, ..., y_p$ such that each y_i is a linear combination of the original components of x and has maximum variance among all y_is that can be formed as linear combination of the x_is. In other words, the PCs $y_1, ..., y_p$ are uncorrelated and carry as much of the information (or variability) from the original variables $x_1, ..., x_p$ as possible. Thus, the PCA reduces a large number of variables to a small set of variables that would explain most of the variability in the original variables.

Let us now denote the ordered pairs of eigenvalues and eigenvectors of Σ by: $(\lambda_1, e_1), ..., (\lambda_p, e_p)$, where $e_i = (e_{i1}, ..., e_{ip})'$ is the i^th eigenvector corresponding to the i^th ordered eigenvalue, λ_i. The PCs are then given by

$$y_1 = e_1' x = e_{11}x_1 + ... + e_{1p}x_p,$$

$$y_2 = e_2' x = e_{21}x_1 + ... + e_{2p}x_p,$$

$$...,$$

$$y_p = e_p' x = e_{p1}x_1 + ... + e_{pp}x_p$$

and the components of the i^{th} eigenvector are at times called loadings of the i^{th} principal

component. The eigenvectors are normalized and orthogonal to each other, i.e., the product $e_i^{'} e_j$ (which is simply the sum of squared loadings for the i^th^ PC) is zero if $i \neq j$ and 1 otherwise. It is known that,
$\lambda_i = var(y_i) = \sigma_{ii}^2$ for $i = 1, ..., p$ and, $\sum_{i=1}^{p} \lambda_i = \sum_{i=1}^{p} var(y_i) = \sum_{i=1}^{p} var(x_i)$.
That is, the total variability in the original variables is equal to the total variability carried by the new linear combinations (i.e., the PCs) and this, in turn, is given by the sum of the eigenvalues. In the following section, we discuss how we can incorporate criticality of information both at the principal component loadings stage and at the raw variable stage.

4 Incorporating criticality at the Principal Component Stage

Suppose with each p variable, we also measure how critical the variable is; that is, observe for each x_i another variable, say on a 0-1 scale, where 0 = non critical and 1 = critical. We could then estimate from the sample data, the likelihood of the i^th^ variable being critical $P(x_i = 1) = P_i$. The value of P_i would be between 0 and 1. Let us also suppose that we develop a criticality index for the i^th^ variable as

$$c_i = P_i \sum_{i=1}^{p} P_i \,. \quad (1)$$

The formula is computed as P_i divided by the summation

The index obtained from equation (1) represents the proportion of criticality likelihood associated with the i^th^ variable (as compared to the total of such likelihoods, summed over all the variables). This index varies between zero and one and if all variables are equally critical then it assigns a criticality of $1/p$ (i.e., reciprocal of the number of variables) to each of the original p variables. Furthermore, $\sum_{i=1}^{p} c_i = 1$.

Now, consider the squared correlation between the j^th^ variable, x_j, and the i^th^ PC, y_i, defined as

$\rho_{ij}^2 = \lambda_i e_{ij}^2 / \sigma_{jj}^2$,

The formula could be interpreted as the proportion of variability in x_j explained by the i^th^ PC y_i [28]. The product of the squared correlation and the criticality index c_j could be used as a measure that incorporates both the criticality of the j^th^ variable and its importance or rank in the i^th^ PC. Therefore, through equation (2), we are able to simultaneously compute both criticality and variability of the original variables:

$$\alpha_i = \sum_{j=1}^{p} \alpha_{ij} = \sum_{j=1}^{p} \rho_{ij}^2 c_j = \lambda_i \sum_{j=1}^{p} e_{ij}^2 \sigma_{jj}^2 c_j \quad (2)$$

Similar to the matrix of squared correlations, $(\rho_{ij}^2)_{i,j}$, which is often used to select the most relevant variables of the original x_i s [2], the matrix $(\alpha_{ij})_{i,j} = (\rho_{ij}^2 c_j)_{i,j}$, $i, j = 1, ..., p$ can be used to select variables that are most critical, among the original variables.

The following procedures could be used to select the most significant set of variables:

- Perform a PCA and compute the quantities α_i and α_{ij}, $i, j = 1, ..., p$ according to equation (2);
- Order the PCs according to the descending order of magnitude of their α_i s, and select the first q PCs that give a desired total of the α_i s, (say, $\sum_{i=1}^{q} \alpha_i = .90$). This is similar to the selection of the first PCs that explain a desired cumulative proportion of variability.
- Arrange the α_{ij} s of the selected q PCs in a descending order of magnitude and select (ignoring repetitions) the q variables that have the largest α_{ij} s.

5 Incorporating criticality at the variable level

The second approach to incorporating criticality information at the variable level is to pre-weight the original variables using Equation (1) and then apply the PCA to the weighted variables. Pre-weighting the original variables is equivalent to weighting the population (or sample) covariance matrix by $p \times p$ diagonal matrix shown below:

$$C = \begin{pmatrix} c_1 & 0 & 0 & \dots & 0 \\ 0 & c_2 & 0 & \dots & 0 \\ .. & .. & .. & \dots & .. \\ 0 & 0 & 0 & \dots & c_p \end{pmatrix}.$$

Therefore, the weighted PCs would be derived from the covariance matrix, $\Sigma_c = C'\Sigma C$ and we could denote them as Criticality Weighted PCs (CWPCs).

In this approach, loadings of the CWPCs as well as the eigenvalues of Σ_c (or the variances of the components) reflect both criticality and variability in the CSFs. When we rank the CWPCs from the highest to the lowest, the first variable or CWPC is the one that carries the most criticality and e most variability among all the CSFs followed by the second variable or CWPC and so on. That is, we can interpret the eigenvalues (or variances) of the CWPCs as the amount of variability-criticality explained by the components.

The following summarize the steps required to selecting the most critical variable from CWPC:

- Multiply the original variables by their criticality indices c_i of Equation (1) and then perform the PCA on the new variables and compute the quantities ρ_{ij}^2 for $i, j = 1, \dots, p$.
- Select the first q PCs that give a desired cumulative proportion of variability explained (say, $\sum_{i=1}^{q} \lambda_i / \sum_{j=1}^{p} \lambda_j$ =.90).
- Arrange the ρ_{ij}^2 s of the selected q PCs in a descending order of magnitude and select (ignoring repetitions) the q variables that have the largest ρ_{ij}^2 s.

6 Validation of the Methodology

6.1 Validation using hypothetical data

As discussed in the introduction, one of the objectives of this paper is to validate the methodology that we have proposed using both a hypothetical data and a real-world data. In this section, we discuss the validation of the methodology using a hypothetical data.

Consider the following covariance matrix related to a population:

$$\Sigma = \begin{pmatrix} 1 & -2 & 0 \\ -2 & 5 & 0 \\ 0 & 0 & 2 \end{pmatrix}.$$

The matrix represents three independent variables x_1, x_2, and x_3 and three component variables y_1, y_2, y_3. From the three independent variables denoted in the matrix, from the perspective of variability, variable number two or x_2 is the most important variable (Please see Table 1 for the Principal Component loadings). According to Table 1, the total variability explained by the three component variables y_1, y_2, and y_3, is 8.000 (5.828 + 2.000 + 0.172 = 8.000). Therefore, the first principal component y_1 explains 73% of the variability (5.828 /8.000) and y_2 explains 25% of the variability.

Table 1. PC analysis showing squared loadings.

	Principal Components		
Variable	y_1	y_2	y_3
	Squared loadings (e_{ij}^2)		
x_1	0.146	0.000	0.854
x_2	0.854	0.000	0.146
x_3	0.000	1.000	0.000
Variance	5.828	2.000	0.172
Cum. proportion	0.729	0.979	1.000

We can use several different approaches to identify the important variables from the PCA. One of these approaches is to choose the most important PCs (e.g., those explaining a cumulative variability of 90% or more). We can then order the squared (or absolute) correlations between the original variables and the PCs and choose the variables with the highest correlation (excluding repetitions). As per this approach, in our hypothetical example, we will choose PCs y_1 and y_2 because they collectively explain 98% of the variability (5.828 + 2.000 out of 8.000). When we order the squared correlations, we will then, select x_2 and x_3 as the two most relevant variables.

At this point, we can consider the criticality matrix $C = diag(.6, .3, .1)$ which shows that x_1 to be the most critical variable followed by x_2. Table 2 reports both the quantities α_i and $\alpha_{ij} = \rho_{ij}^2 c_j$. The α_i indicates that when the PCs are ordered as before, the first variable x_1 (0.512) to be the most important variable followed by the second variable x_2(0.298). Table 2 also shows that the two PCs, x_1 x_2, have cumulative α of 91% (0.810 + 0.100). We, therefore, choose x_1, x_2, as the two most important variables from variability-criticality point of view.

Table 2. PC analysis showing squared correlations and squared correlations times criticality indices

	Principal Components		
Variable	**y_1**	**y_2**	**y_3**
	Squared correlations (ρ_{ij}^2)		
x_1	0.854	0.000	0.146
x_2	0.995	0.000	0.005
x_3	0.000	1.000	0.000
	The quantities ($\rho_{ij}^2 c_j$)		
x_1	0.512	0.000	0.088
x_2	0.298	0.000	0.002
x_3	0.000	0.100	0.000
α	0.810	0.100	0.089

We can now use the CWPC approach, where we first weight the original variables x_1, x_2, x_3 by the matrix C and then perform a PCA.

Table 3. Criticality weighted PC analysis (CWPCA) showing squared loadings correlations

	Principal Components		
Variable	**y_1**	**y_2**	**y_3**
	Squared loadings (e_{ij}^2)		
x_1	0.438	0.562	0.000
x_2	0.562	0.438	0.000
x_3	0.000	0.000	1.000
	Squared correlations (ρ_{ij}^2)		
x_1	0.934	0.066	0.000
x_2	0.959	0.041	0.000
x_3	0.000	0.000	1.000
Variance	0.768	0.042	0.020
Cum. proportion	0.925	0.976	1.000

Table 3 reports the squared loadings and correlations along with eigenvalues and cumulative proportion of variability explained by each CWPC. In this approach, the first CWPC explains about 98% of the total variability and as per the process explained in Section 3.2., we will again select x_1, x_2 as the most important variables. This conclusion is consistent with our earlier two approaches. We must caution that this type of perfect agreement among the various approaches is not always true. We will discuss this issue further in the next section

7 Validation using empirical data

In this section, we will discuss the validation of the methodology using a real-world data on CSFs. The data set for this analysis was obtained from a recently completed empirical study conducted by the first author. The study used 203 auditors with experience in e-commerce audit (B2B audits) to give their perceptions about the various CSFs that are important to an auditor to perform a B2B audit efficiently. The measurement scale consists of 38 items/variables placed in random order in the questionnaire and each variable is measured on a 5-point Likert. For simplicity, we label the variables 1 through 38.

Each auditor-respondent was asked to indicate their perceptions on a 5-point Likert Scale about how critical each variable was for a successful performance of an E-commerce audit. Once the 203 responses were collected, we converted the corresponding criticality by dichotomizing the criticality variable into a zero-one variable (1 if the Likert score was 4 or 5 and 0, if otherwise). Although this would result in losing some of the information content, we resorted to this procedure purely for the sake of brevity in explaining the methodological approach. However, the methodological process that we discus is capable of handling continuous variables but, it would be far more elaborate than what is explained in the paper.

For each of the 38 dichotomized questions, we estimated the P_i (correlated variables measuring certain characteristics or judgments of individual attributes in a population).

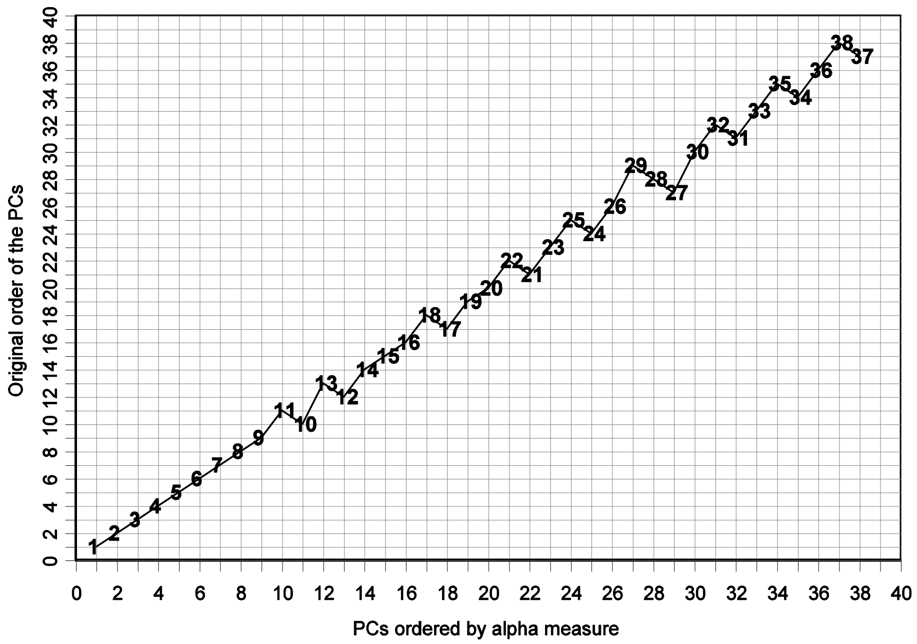

Fig. 1. Plot of order of the original principal components vs. their order according to the α measure in equation (2)

Figure 1 shows the ordering of the PCs according to their α_is of equation (2). We found that the first 20 PCs to explain 90% of the variability. Therefore, we extended our analysis further to identify the first 20 variables by importance from among the 38 variables used in the study.

Table 4 shows the rank ordering of the first twenty variables in the order of highest to the lowest criticality along with Criticality Weighted PCs (CWPC). Column no. 2 shows the ranking of the variables from high to low ranking and by their variable numbers. The third and the fourth columns represent the ranking of each of these variables according to CWPC and α measures, respectively. Columns three and four, for example, point out that, variable no. 37 is the most critical according to both CWPC and α rankings (Columns 3 and 4 respectively). In contrast, variable no. 36 is ranked as second by the criticality approach (Column 2) and as 3rd by CWPC and as 5th by the α approach (Columns 3 and 4 respectively). Variable no. 35, ranked by criticality approach as the 3rd most important, is not even ranked within the top 20 variables either by the CWPC or α approaches. The CWPC approach, when compared to the criticality approach, fails to capture 7/20 (35%) of the twenty most critical variables, while the α approach fails to capture 5/20 (25%) of the twenty most critical variables. In Table 4, the letters NA indicates that the variable is not ranked in the top 20 according to either CWC or α approaches. We must point out that, if we are interested in capturing a significant proportion of the variance (e.g. 90%), we must consider all 34 ranked PCs that collectively explain 90% of the variability and criticality and not restrict ourselves to just the 20 critical variables shown in Table 4. Column 3 and 4 report the rankings of the variables in Column 2 according to the CWPCA and the α-measures, respectively.

Table 4. The most important 20 variables based on criticality alone (second column) and on PCA (fifth column)

index	Criticality	CWPC	ALPHA	PCA	CWPC	ALPHA
1	37	1	1	37	1	1
2	36	3	5	27	10	3
3	35	NA	20	38	2	2
4	18	NA	11	32	7	6
5	16	15	NA	26	11	4
6	38	2	2	22	12	7
7	15	13	18	33	6	8
8	19	NA	NA	36	3	5
9	26	11	4	24	4	9
10	34	9	15	25	5	10
11	25	5	10	14	8	13
12	22	12	7	23	14	12
13	17	NA	17	29	20	14
14	5	NA	NA	18	NA	11
15	33	6	8	3	18	16
16	32	7	6	1	NA	NA
17	24	4	9	28	NA	19
18	8	NA	NA	34	9	15
19	6	NA	NA	2	NA	NA
20	27	10	3	17	NA	17

Similarly, columns 6 and 7 report the rankings of the variables in column 5. Column 1 is a sequential index to facilitate easier reading of the table.

When we consider the top 34 variables ranked by each method and by PCA and criticality approaches, we find that the CWPCA approach fails to capture 4/34 (12%) of the critical variables; the PCA approach fails to capture 3/34 (9%) of the critical variables while, the α approach fails to capture only 3/34 (9%) and 2/34 (6%) of the critical variables respectively. These results make us conclude that the α measure may be the most accurate compared to the CWPCA.

8 Summary and Conclusions

In this paper, we presented a theoretical framework for measuring the criticality of success factors, in the context of an information system audit. We proposed an analytical procedure that would compute the criticality of variables, procedures, and processes. The analytical procedure provided a means to weight the perceived criticality of a success factor. We developed the analytical procedure with the intent of overcoming some of the limitations of CSF methodologies pointed out in the literature. The methodology that we proposed is less subjective and could be applied to any empirical study that examines perceptions, outcomes of respondents or processes in the context of criticality.

We proceeded on the basis that we could obtain perceptional responses from individuals on factors that they consider critical. Identification of success factors is subjective and cannot be avoided. However, our methodology proceeded on the basis that we can independently and objectively measure the criticality of the success factors identified by the respondents and that by using Principal Component Analysis (PCA), we could assign weights and use the weights to differentiate between critical and non-critical attributes.

The process required that we obtain individuals' to respond on two separate five-point Likert scale instruments indicating whether certain attributes related to an information system audit a B2B ecommerce audit) are 1) important success factors and 2) if so, whether the factor that they identified is also a critical factor. We analyzed the responses from the first Likert instrument, using PCA so that we can ascertain the importance of each success factor (based on their relative variances). Later, using the success factors we identified from the first analysis, we proceeded with a second stage analysis in which we measured the criticality of each success factor. The first analysis is a direct method and is used to calculate the PCA weights (loadings) that also produce a criticality index. The second analysis is an indirect method and involves assigning weights to the original observations (or variables) in the study and then applying the PCA to the weighted variables. Thus, the two-stage analysis involved both a subjective and objective determination of the criticality of variables.

Once we computed the PCA weights, criticality index, and had identified the criticality of the variables, we performed further analysis to validate the methodology. The validation required that we use both a hypothetical data and a real-world data. The real-world data was obtained from a recently completed empirical study conducted by the first author. The measurement scale consisted of 38 items/variables placed in random order in a questionnaire and each variable was measured on a 5-point Likert.

Applying the methodological procedures we had developed and explained in the paper, using the hypothetical data, we were able to identify two variables that collectively explained 98% of the variability. We concluded that the two variables that were most critical for the success of an information system audit. We then weighted the original variables and again applied the PCA to the weighed variables. Our results showed that the two variables that we had identified from the earlier subjective assessment to be identified as critical variables again. While this result using the hypothetical data was a 100% validation of the methodology we had proposed, we were cautious to point out that such perfect agreement is not always be possible.

We later repeated the validation of the methodology using real-world data on CSFs. We estimated the P_i (correlated variables measuring certain characteristics or judgments of individual attributes in a population) for the 38 questions used in the survey. Our analysis showed that the first 20 PCs to explain 90% of the variability and also provide a ranking of the 20 variables from the highest to the lowest order in terms of critical importance. When we compared the results to the various measurement factors that we had used, we found the rankings not be consistent across measurement scales. While some variables were consistently ranked as most important or critical, other variables were not even identified as the top 20 critical variables by some of the measurement approaches. For example, the CWPCA approach failed to capture 35% of the top 20 variables that were most critical according to the criticality measure while, the α measure failed to capture only 25% of those variables. On the other hand, CWPC and the α measure failed to capture 25% and 10%, respectively, of the top 20 most important variables according to the PCA. Thus, we can conclude that the α measure appears to more accurate than the CWPC as it captures greater proportion of both variability and criticality. Of course, PCAs and criticality measure are designed to capture variability and criticality alone, respectively, and therefore, although they capture larger proportion of these two features than the α measure does, they should not be preferred over the α measure, as the latter is designed as a combined measure of both features.

The methodology we had proposed appeared to work well and is useful when a large number of variables have to be ordered according to their importance both from their membership in the success factors list and from their criticality. The proposed methodology is heuristic and needs further development. Currently, as it is proposed, it suffers from certain limitations. One of the major limitations is that we converted the five-point Likert scale responses to a binary variable. This could result in information loss. In future, we must extend the process to be able to measure continuous and ordinal scales. This would require modification of the α in equation 1.

In conclusion, we can state that our paper is an attempt at developing a methodology for measuring success factors and their criticality with less subjectivity than has been attempted in prior literature. We believe that the proposed methodology makes a contribution to the IS literature in the area of information system performance evaluation.

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Jagdish PATHAK is Associate Professor of Accounting & Systems at the Odette School of Business Administration, University of Windsor, Ontario, Canada and the lead author of this research project. He has a PhD in Management Studies majoring in accounting and MIS from the University of Goa.He is an award winning author in his domain of research publishing in scholarly and professional journals internationally. His papers have appeared in the Journal of Accounting and Public Policy (Elsevier), International Journal of Auditing (Wiley), Information Systems Management (Taylor & Francis), Managerial Auditing Journal (Emerald) and several other. Dr. Pathak is *Editor* (*North America)* of the *Managerial Auditing Journal* and *Associate Editor (Accountancy*) of the *International Journal of Applied Decision Science* (Inderscience). He has published two research monographs from Allied (New Delhi) and Springer Verlag (Berlin) on the information technology auditing. His current research interests are in the areas of technology assurance, enterprise systems impact on firms' performance, international corporate governance, investor protection, and investor behaviour with respect to internet-based financial disclosures.. He is an active member and nominated executive of strategic and emerging technology and the information systems sections of the American Accounting Association. He can be contacted at jagdish@uwindsor.ca.

Abdulkadir HUSSEIN obtained PhD in Statistics from University of Alberta in Edmonton, Canada, in 2003. He is an associate professor at the University of Windsor, Ontario Canada and currently visiting associate professor at King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia. His areas of research interest are: Biostatistics, Statistical quality control, Healthcare outcomes research, Mixture models, and Sequential analysis in clinical trials. He has published more than 20 peer reviewed journal articles.

Ram SRIRAM is Controllers RoundTable Distinguished Professor at the School of Accountancy, Robinson College of Business, Georgia State University, Atlanta. He earned his doctorate in 1987 from University of North Texas. He is also a Certified Public Accountant (CPA). He is also a visiting professor at Cairo University, Egypt, Great Lakes Institute of Management, India and Indian Institute of Management, Bangalore. He is the author of more than 60 articles in leading journals such as Management Science, Decision Sciences, Accounting Organizations and Society and others. He specializes in information system theories and methodologies as they relate to accounting issues. Ram serves in the editorial boards of several leading academic journals including the Journal of Information System, International Journal of Accounting Information Systems

Ejaz AHMED is Professor and Head of the Department of Mathematics and Statistics at the University of Windsor. He is a founding Director for Centre for Statistical Consulting, Research, Learning and Services (CSCRLS). Dr. Ahmed has inducted as a Fellow of American Statistical Association in 2009. He is an elected member of the International Statistical Institute and a Fellow of the Royal Statistical Society. He is the book review Editor of Technometrics. Dr. Ahmed serves as an Associate editor of several international statistical journals, including Computational Statistics and Data Analysis (CSDA) and Journal of Statistical Computation and Simulation (JSCS). He was a guest co-editor for Linear Algebra and its Applications (LAA). He served as a Board of Director and Chairman of the Education Committee of the Statistical Society of Canada. His area of expertise includes statistical inference, asymptotic theory, statistical education and consulting. He has over 100 published research articles in scientific journals. Further, he co-edited two volumes and organized many sessions and workshops. Recently, he co-authored a textbook on probability and statistics. He made over 100 invited scholarly presentations in various countries around the globe. He supervised several graduate students including Ph.D. students.