CIO Executive Risk Behavior Model

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CIO Executive Risk Behavior Model

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ABSTRACT
As evidenced in a broad-based body of research, risk affects decision-maker’s behavior by influencing perceptions of decision situations, evaluation of alternatives, choices made, and other decision-related actions taken in response to risk. Based on theory from risk literature, a conceptual model was identified and tested. The data for this study was collected using a stratified random sample from the top Chief Information Officer (CIO) of the banking industry. The survey instrument collected information pertaining to the CIO executive’s risk behavior preference. The analysis of the data was used to determine an effective risk behavior model that can be used for future business decision making process. It is the anticipation that this model can be used to determine the CIOs risk behavior in decision making that would impact the information systems (IS) strategy. The CIOs risk behavior model tested indicated evidence supporting the proposition that both risk propensity and risk perception influenced the ultimate risk behavior of the CIO executive that influences the decision making process. These findings signify that the proposed CIOs risk behavior model is robust.

Keywords
CIO, Risk behavior, Propensity, Perception, Decision Process, Structural Equation Modeling, information systems strategy, Alignment.

INTRODUCTION
Research in the area of decision-making and how it influences the behavior of the decision maker will allow corporations to identify areas where the individuals making the decision can be enhanced. Moreover, top executives may want to identify these behavioral influences to increase the information strategy. IS strategic alignment is directly related to the CIOs of the organization. By recognizing ways that can inhibit or optimization of the IS strategic alignment, top executives can then generate and adopt new management practices and policies for increasing the IS strategic alignment and increase the organizations business value. Therefore, in any top executive position, there are behavioral influences that exist in the decision making process. This paper explores the CIOs risk behavior that influence their executive decision making process.

BACKGROUND
CIO Executive Risk Behavior
Scholars know little about how executives select risky action, although such decisions are the essence of strategic choice (Palmer, 1999). Risky decision making understandably attracts research interest because of its importance and because of the challenges it presents to researchers (March, 1992). Researchers still have difficulty explaining (let alone predicting) decisions made under risk (Ghosh, 1992; Thaler, 1990). Decision makers may differ on risk taking behavior because they differ on interpretations of the eccentricity about a decision (Krueger, 1994). This coincides with research evidence that indicates individuals’ perceptions of risky situations may explain why they engage in risky behavior (Sitkin, 1995). This study takes the position that risk is an inherent characteristic of all strategic decisions and must be viewed from an individual behavioral perspective if researchers hope to gain an appreciation of managerial expectations regarding the risks of a particular decision.

By examining Sitkin and Pablo’s (1992) risk definition, “Risk is a characteristic of decisions that is defined as the extent to which there is uncertainty about whether potentially significant and/or disappointing outcomes of decisions will be
realized" (p.10) it becomes evident that all decisions have inherent risks. The more uncertain decision outcomes are, the harder decision goals are to achieve, and the more extreme the gain or loss potential of the decision. Therefore, the level of uncertainty in the decision will influence the level of risk.

As evidenced in a select body of research, risk affects decision behavior by influencing perceptions of the decision situation, evaluation of alternatives, choices made, and other decision-related actions taken in response to risk (Antonides, 1990; Pablo, 1996; Sarasvathy, 1998; Weber, 1997). Managers’ assessments of the risk dimensions of a decision are central to managerial behavior with regard to that decision (March, 1987; Pablo, 1999; Papadakis, 2002; Sullivan, 1997).

Top IS executives must carefully evaluate their decision making process because of the underlying behavior characteristic of taking risks, if not they could face damaging consequences. Since information systems change so rapidly, many CIO executives find it difficult to keep pace with new developments (Prattipati and Mensah, 1997). Therefore, before investing in information systems, executives should carefully evaluate the information system within the organization and within the organization’s goals and mission. By carefully evaluating the information system, a clear understanding of what the information system can do and cannot do is possible. Careful evaluation is necessary to avoid investing in a system that is out of alignment with the organization and its business vision (Kottemann and Konsynski, 1984). Failure to have a clear understanding of the information system introduces uncertainty in the decision process that may cause an investment disaster.

Risk is an inherent characteristic of all strategic decisions in that some degree of uncertainty is associated with the decisions outcomes. As with all outcomes, some outcomes are more desirable than others (Pablo, 1996). With increasing levels of uncertainty there is an increased perception of situational riskiness (Williams, 1999). Moreover, researchers found that the expectation of the amount of possible disappointment related to specific outcomes influences situational riskiness. Even positive expected outcomes can be perceived as risky if they are relatively difficult to achieve or unlikely to be realized (March, 1987; Sitkin, 1992).

By examining the decision-making processes of CIO executives, variations in strategic alignment may be revealed (Antonides and Van Der Sar, 1990; Baird and Thomas, 1985; Das and Teng, 2001; Forlani and Milliman, 2000). As decision makers, executives’ views towards a decision vary by their individual behavior towards the decision (Williams and Narendran, 1999; Webber and Milliam, 1997; MacCrimmon and Wehrung, 1990). Because all decisions have inherent risks, risk influences the executives’ perspective of the decision by the perceived degree of uncertainty of the outcome (March and Shapira, 1987; Pablo and Sitkin, 1996). These inherent risks vary in range from minimal to extensive and affect the CIO executives’ decision-making process (Pablo and Sitkin, 1996; Pablo, 1999).

**The Concept of Risk Behavior**

The literature on individual risk behavior contains two distinct research threads on risk decision-making. Personality psychologists place an emphasis on individual differences in risk taking (Das, 2001; Williams, 1999; Brockhaus, 1980). They tend to credit risk behavior to the common traits and nature of each individual decision maker. Researchers have observed that individuals are reasonably consistent in their attitudes towards risk (March and Shapira, 1987; Weber and Milliman, 1997). Individuals with a risk-seeking characteristic seem more comfortable with risk taking than others (Forlani, 2000). This allows researchers to differentiate between types of decision makers in terms of their risk propensity. Individuals can be classified as either being a risk seeker, risk neutral, or being risk averse. A number of researchers also believe that the individual’s risk propensity can explain the risk behavior of that individual.

In contrast, personality psychologists and experimental psychologists dispute the individual risk propensity notion and argue that situational factors have a greater influence on individual risk behavior (Kahneman, 1979). Experimental psychologists further argue that the risk propensity of decision maker appears to lack consistency across all decision making situations (MacCrimmon, 1990; Schoemaker, 1993). Experimental psychologists attempt to understand universal risk behavior and argue that external stimulus produces reasonably consistent results. Several empirical studies suggest that situational factors, such as outcome history and decision framing are significant in determining the perceived risks in a decision (Kahneman, 1979; Thaler, 1990). For these reasons, the views of experimental psychologists have considerable support in understanding risk behaviors in the decision making process.

Given solid theoretical development and considerable empirical support for both positions, efforts have been made to integrate both of them. (Baird, 1985; Sitkin, 1992). These studies suggest that the risk propensity of the individual interacts with situational factors of risk perception to determining risk behavior (Figure 1). The dotted path indicates a contradiction in the literature between risk perception and risk behavior (Sitkin and Pablo, 1992).
The Sitkin and Pablo (1992) risk behavior model encompasses both approaches (risk propensity and risk perception) and illustrates the subcomponents of each. The upper part of the model is that of risk propensity, which corresponds to the personality psychologist’s view.

Risk propensity, the “willingness to take risks” (Sitkin, 1995), is composed of risk preference, inertia, and outcome history. Risk preference is based on an individual’s experience and beliefs that make up his/her attitudes about risk itself. Although risk preference is considered stable, inertia and outcome history tend to be more dynamic. Inertia is associated to the momentum of outcomes. This translates into the notion that outcomes are perceived to be continuously consistent and forms a series of positive or negative trends in succession. Outcome history is very similar to inertia, but it is perceived as either a sum or average of past risk decision outcomes. The outcomes are perceived either overall positive or overall negative in description.

The risk perception section of the Sitkin and Pablo (1992) model corresponds with the experimental psychologists’ argument that risk behavior is largely determined by situational elements of each unique risk occurrence (risk perception). The risk perception section consists of the subcomponents of problem framing, top management team homogeneity, social influences, problem domain familiarity, and organizational control systems.

In the review of the literature, previous work suggested that risk perceptions and risk propensity may best be viewed as mediating the affect of a variety of other variables on risk behavior. Yet, the literature on the relationship between risk propensity and risk perception on risk behavior is conflicting (Sitkin and Pablo, 1992). This ambiguity indicates a need for empirical testing. The literature relationship paths between risk propensity, risk perception, and risk behavior are indicated in the Sitkin-Pablo (1992) conceptual model (Figure 1).

**METHODS AND RESULTS**

**The Targeted Industry**

The questionnaire was targeted to an industry which has a critical need for CIO executive decisions towards Information Systems. These two industries identified were health and financial services both of which are prime examples of high IS environments. Of the two industries, the financial sector was preferred. The preference of using the financial industry was due to the fact that the financial industry is fast paced and dynamic within a competitive environment as well as having additional information publicly available.
**Data Sample Selection**

The population consisted of top level CIO executive officers from financial institutions who were members of the US Federal Banking Reserve. The Federal Banking Reserve District provided a public listing of its holding banks. The Federal Banking Reserve District list used included only financial institutions from the United States. The holding banks from the list were selected, since they are the main parent bank of groups of banks. After reviewing the holding bank population, it was determined that using a stratified random sample method would be the best approach to sample the population as this would assume we had bank holding companies that are large, medium and small.

Using the Federal Banking Reserve website, a list of the holding companies addresses with their total assets was obtained. The list contained 5,052 holding company banks which served as the total population of the industry. The names were verified and matched with their appropriate total assets. To stratify the population, a federal reserves definition of classification of bank sizes was implemented. Using the federal reserves classification of bank sizes, the holding banks were categorized accordingly. The banks within the categories would then be randomly selected in proportion to the population.

There are five federal bank categories: 1) under 25 million, 2) 25 to 49.9 million, 3) 50 to 149.9 million, 4) 150 to 300 million, and 5) over 300 million in total domestic assets. All 5,052 banks were grouped as follows: 1st category there were 390 holding banks, 2nd category there were 779 holding banks, 3rd category there were 1,937 holding banks, 4th category there were 940 holding banks, in the 5th category there were 1,006 holding banks.

A target of 250 responses was determined necessary based on the statistical analysis methods to be conducted on the responses (Hair, 2006). Prior research surveys indicated that a total typical response rate expected was that of a 10% return on the administered instruments. Therefore, it was determined that a sample size of 2,500 would be needed to achieve the desired goal of 250 responses.

Following the distribution of the bank size categories in proportion to the population, it was calculated that from the 2,500 random samples needed, 7.7% of the random samples would be needed for the 1st category, 15.4% would be selected randomly for the 2nd category, 38.3% would be selected randomly for the 3rd category, 18.6% would be selected randomly for the 4th category, and 19.9% would be selected randomly for the 5th category.

This resulted in a sample distribution of 193 banks for the 1st category, 385 banks for the 2nd category, 959 banks for the 3rd category, 465 banks for the 4th category, and 498 banks for the 5th category. These survey instruments totaled the 2,500 banks that composed the stratified random sample.

**Statistical Analysis**

The responses of the questionnaires were compiled and examined. As with any research study, the compiled data was examined prior to analysis. By examining the data, a better understanding of where it came from (descriptive statistics), if it had an administration issues (potential bias), how well it reflected the questionnaire (reliability), and how well it measured what the researcher intended it to measure (validity) may be determined. These initial examinations of the response data provided insights to usability and potential issues that affected the statistical analysis. The initial examination of the data for some statistical tools was a prerequisite in determining whether that statistical tool was appropriate to use. The statistical tool best suited for this study is structural equation modeling (SEM). SEM requires that, prior to its implementation, preliminary analysis be done to determine its usability and other special issues that might bias the results.

**Characteristics of the Sample**

Total banks surveyed were 2,500 in the stratified sample. Since each bank received two mailings, a total of 5,000 questionnaires were mailed. The questionnaire was addressed to the Chief Information Officer / IS manager. Mailings returned as undeliverable totaled 153. Responses collected from the survey totaled 187. Three of the instruments that were sent in by fax had incomplete data and therefore were removed from the data set. Therefore, the total 187 were adjusted to a usable set of 184. This process of elimination of incomplete data sets is an example of complete case approach also known as listwise or complete data approach (Hair et al., 2006). Listwise is the simplest and most direct approach for dealing with missing data. Listwise data sets only include those observations with complete data.

All the response distribution categories, with the exception of category 4, was within 5% of the target population distribution. However, category 4 had an 11% deviance than the actual population. The ranges of the respondents varied from working in the current position from 1 to 35 years, working in the industry for 2 to 42 years and the holding bank sizes varied from 2 to 600 employees. The average respondent (mean) worked in their current position for approximately 13 years, worked in the industry for 22 years and the average size of the holding bank consisted of 89 employees (Table 5.2).
Reliability and Validity

Reliability has importance because of its relationship to the validity of the survey. While reliability is about the measurement, validity is about the relevance and usefulness of what is measured. It is possible for a survey to be reliable and to measure the same thing consistently with precision and for what it measures to be of no use for the study. However, it is not possible for survey results to be valid if the data is not reliable. It is important to understand that reliability and validity are not measured but estimated.

Although most of the items measuring these constructs have been used in past research, these scales had not been used within the context of the proposed study. Consequently, assessing the reliability and validity of the scales prior to hypotheses testing was necessary.

Estimation of Reliability

The reliability of each scale was estimated by calculating Cronbach’s α (Cronbach, 1951), and composite reliability (Fornell, 1981). Cronbach’s α tests the internal consistency of the individual scales. The Cronbach’s alpha statistic measures the internal consistency of a single factor by the level of correlation between the indicator variables that describe the factor. This method is based on the assumption that variables measuring the same construct should be highly correlated with one another. Hence, the method provides a measure of the internal consistency of the construct (Nunnally, 1994). Modest reliability estimates of .70 or higher is acceptable in the early stages of construct validation, but higher reliability estimates of .80 are sufficient for most basic research (Nunnally, 1994). This study examines Cronbach’s alpha statistic and Item-to-Total correlation to estimate the reliability of the scales used.

The initial reliability analysis of the items measuring risk propensity was examined. First analysis of risk propensity revealed that item 04 should be deleted based on item-to-total correlations. After deleting item ciorbq04, the remaining items were retested. These results indicated that item 05 did not meet the item-to-total correlation of at least .30; therefore, item 05 was deleted and the remaining items were retested. The remaining items 01, 02 and 03 met the reliability criteria (Cronbach’s alpha = .79). Consequently, a three-item measure of risk propensity was available for further analysis.

The initial reliability analysis of the items measuring risk perception was examined. Based on the item-to-total correlations, no items were trimmed. Therefore, no adjustments were made to the initial reliability analysis. As the table indicates, items 06, 07, 08 and 09 had an alpha of .83 which meets the reliability criteria of being higher than a Cronbach’s alpha of .60. Therefore, all 4 items of the measure of risk perception were available for further analysis.

Estimation of Validity

The difference between validity and reliability is that validity is concerned with how well the concept is defined by the measures, whereas reliability relates to the consistency of the measures. Therefore, estimation of validity is the examination of to the extent to which a measure or set of measures correctly represents the concept of the study (Hair, 2006). Therefore, it is possible to determine the ability of the questions in a questionnaire to adequately reflect the construct they were intended to represent. This is typically accomplished by using the statistical tool of factor analysis. By using factor analysis, the questions used to measure a construct should form one factor that represents that construct. Questions that do not ‘load’ with the others or have low ‘loadings’ can therefore be identified and properly addressed.

The two subdimensions of CIOs risk behavior were confirmed by subjecting the seven items from the validity testing to measuring CIOs risk behavior to a maximum likelihood factor analysis. The factor loadings indicated that there were two subdimensions of CIOs risk behavior. Items 01, 02 and 03 loaded on one factor (labeled as “Risk Propensity” in the literature). Items 06, 07, 08 and 09 loaded as on factor (identified in the literature as “Risk Perception”).

Empirical Modeling

Due to the nature of the proposed model, the statistical tool best suited to evaluate the model is structural equational modeling. Many models in the literature that examine similar areas use partial least squares (PLS). This study is different in that it uses SEM to examine the proposed model. The difference between SEM and PLS is that PLS assumes that there is no measurement error while SEM uses latent variables to account for measurement error. Measures are often imperfect and contain measurement error. Measurement error will bias parameter estimates, and the bias does not go away as the number of observations increases. Use of SEM makes it possible to identify errors of measurement and remove them from the data decreasing any bias in the results that might occur.
Structural Equation Modeling

Structural equation modeling is an all-inclusive statistical method used by researchers in various social sciences. This statistical method can be used to test research hypotheses in terms of presumed cause-and-effect variables and indicators of latent variables (Jöreskog, 1993). Structural equation modeling has the ability to directly incorporate explicit estimation of measurement error and also has the ability of addressing questions about score validity because the theoretical models are directly tested.

According to Gerbing and Anderson (1988), it is appropriate to adopt a two-step procedure when implementing SEM. The steps followed should be to first estimate the measurement model then perform a simultaneous estimation of measurement of the structural model. The purpose of first estimating the measurement model is to determine how well the observed indicators serve as a measurement instrument for the latent variables. If the first step is within acceptable parameters, then a path analysis can be done to determine the relationships among the constructs. This was the SEM two-step statistical procedure performed in this study.


Following the two step approach of Structural Equation Modeling (SEM), the measurement model is first analyzed. The goal of a measurement model is to describe how well the observed indicators serve as a measurement instrument for the latent variables. The key concepts here were measurement, reliability, and validity. These concepts are best scrutinized using the goodness-of-fit measures.

The original Sitkin-Weingart (1995) model was a preliminary test for several key aspects of the Sitkin-Pablo (1992) model. The Sitkin-Weingart (1995) model tested used 38 business administration master degree students. As a result, the Sitkin-Weingart (1995) has not been extensively tested beyond preliminary testing. Therefore, it is important to retest the model using a larger and random selected data set. Using the data set collected from CIOs of the holding banks, the Sitkin-Weingart (1995) model was subjected to the measurement model analysis. The Sitkin-Weingart measurement model results are presented in Figure 2 and Table 1.

![Diagram](image-url)

Figure 2 Sitkin-Weingart Measurement Model
Table 1 Goodness-of-Fit for Sitkin-Weingart Measurement Model

<table>
<thead>
<tr>
<th>Goodness-of-Fit Measure</th>
<th>Measurement Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute Fit Measures</td>
<td></td>
</tr>
<tr>
<td>Likelihood-ratio chi-square ($\chi^2$)</td>
<td>176.82</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>71.00</td>
</tr>
<tr>
<td>Goodness-of-Fit Index (GFI)</td>
<td>0.89</td>
</tr>
<tr>
<td>Adjusted Goodness-of-Fit Index (AGFI)</td>
<td>0.84</td>
</tr>
<tr>
<td>Noncentrality Parameter (NCP)</td>
<td>105.82</td>
</tr>
<tr>
<td>Normed Fit Index (NFI)</td>
<td>0.83</td>
</tr>
<tr>
<td>Relative Fit Index (RFI)</td>
<td>0.78</td>
</tr>
<tr>
<td>Root Mean Square Error of Approximation (RMSEA)</td>
<td>0.09</td>
</tr>
<tr>
<td>Normed chi-square ($\chi^2/df$)</td>
<td>2.49</td>
</tr>
<tr>
<td>Expected Cross-Validation Index (ECVI)</td>
<td>1.34</td>
</tr>
</tbody>
</table>

The three different categories of goodness-of-fit measures indicated a comparatively good fit. Although the indices varied, the comprehensive overview indicated not a perfect fit but a consistent goodness-of-fit that was acceptable within the exploratory range. Although the goodness-of-fit indices could have been improved by removing several of the items, it was decided that the model not be trimmed to retain as many of the original items as possible.

The Absolute Fit Measures indicate that a majority of the indices are at or just below the common accepted range of .90, but well within the exploratory range of .75. The Goodness-of-Fit Index (GFI) was .890 and the Adjusted Goodness-of-Fit Index (AGFI) was slightly lower at .837. The Bentler-Bonnet Normed Fit Index (NFI) was similar to the AGFI and was .831 with the Relative Fit Index showing the lowest index at .784. The next Absolute Fit Measure examined was the Root Mean Square Error of Approximation (RMSEA). The RMSEA was .090, which is just outside the commonly accepted range of .05 - .08. The last Absolute Fit Measure examined was the Normed chi-square ($\chi^2/df$). The Normed chi-square value shows a very close fit using the common Normed chi-square is 2.49, which is better than the generally accepted ratio of 3 and the more liberal ration of 5.

Sitkin-Weingart Path Model

After testing the Sitkin-Weingart (1995) measurement model and the results being favorable, the Sitkin-Weingart (1995) model was then subjected to path analysis. The analysis would assist in the understanding and usability of the model and its potential impact in the combined model study. The Sitkin-Weingart Path Model results are presented in Figure 3 and Table 2.

![Figure 3 Sitkin-Weingart Path Model](image-url)
Table 2  Goodness-of-Fit for Sitkin-Weingart Path Model

<table>
<thead>
<tr>
<th>Goodness-of-Fit Measure</th>
<th>Measurement Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute Fit Measures</td>
<td></td>
</tr>
<tr>
<td>Likelihood-ratio chi-square ($\chi^2$)</td>
<td>45.64</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>13.00</td>
</tr>
<tr>
<td>Goodness-of-Fit Index (GFI)</td>
<td>0.97</td>
</tr>
<tr>
<td>Adjusted Goodness-of-Fit Index (AGFI)</td>
<td>0.93</td>
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<tr>
<td>Noncentrality Parameter (NCP)</td>
<td>32.64</td>
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<tr>
<td>Normed Fit Index (NFI)</td>
<td>0.95</td>
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<tr>
<td>Relative Fit Index (RFI)</td>
<td>0.91</td>
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<tr>
<td>Root Mean Square Error of Approximation (RMSEA)</td>
<td>0.08</td>
</tr>
<tr>
<td>Normed chi-square ($\chi^2/df$)</td>
<td>3.51</td>
</tr>
<tr>
<td>Expected Cross-Validation Index (ECVI)</td>
<td>0.21</td>
</tr>
</tbody>
</table>

The Absolute Fit Measures disclosed that a greater part of the indices for the model all reveal a good fit. The Normed Chi-square is 3.51, which is just above the generally acceptable range of 1 to 3, yet well within the more liberal range of 1 to 5. The Bentler-Bonnet Normed Index (NFI), which indicated the proportion in the overall fit of the absorptive capacity model to a null model is .947. The Goodness-of-Fit Index (GFI) was .968 and the Adjusted Goodness-of-Fit Index (AGFI) was to some extent lower at .931. The next Absolute Fit Measure researched was the Root Mean Square Error of Approximation (RMSEA) The RMSEA was .083, which was slightly outside the commonly accepted range of .05-.08. The Expected Cross-Validation Index (ECVI) is .206.

The goodness-of-fit indices indicated a comparatively good model fit. Due to the fact that the numerous fit indices were favorably high, the model fit was considered to be robust.

DISCUSSION AND CONCLUSIONS

Sitkin-Weingart Model

Sitkin and Weingart presented two sets of two model relationships for a total of four possible relationships. Each relationship in the model was retested and shown to be supported. These findings are important in that there were no other confirming studies done to test these relationships and that there were any using an SEM approach in testing. The relationships tested indicated evidence that suggests risk propensity and risk perception influences CIO risk behavior. In conclusion, the Sitkin-Weingart risk behavioral model is a robust and usable model for future studies exploring the risk behavior.

Implications / Future Research

The results emphasize the prominent role that risk propensity and risk perception influences CIO risk behavior and the relationship that exists between these concepts. Given that CIO risk behavior influences the executive’s decision making process, the next stage of future research would be the examination of the relationship between various executive’s risk behavior and their decision making process. This might lead to further expansion of the CIO risk model and other models that encompass the CIO decision making process.

These findings suggest that are other similar areas of future research necessary to expand the deficit in the research literature of risk and decisions. The study was designed to indicate and test a measurable CIO behavioral risk model, particularly at the executive level. Because high level CIO executives have a bird’s eye view, their decision making process has a trickle down effect throughout the entire organization. A more detailed analysis and additional research can investigate similar behavioral characteristics other than CIOs risk behavior that might impact the executive decision making process and its impact on the organization.
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