Internal Control Risk Assessment System Using CRAS-CBR

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Abstract

Information Technology (IT) and the internet have been major drivers for the changes in all aspects of the business processes and activities. They have brought major changes to the financial statements audit environment as well, which in turn has required modifications in audit procedures. There exist, however, certain difficulties with current audit procedures especially for the assessment of the level of control risk. This assessment is primarily based on the auditors' professional judgment and experiences, not based on the objective rules or criteria. To overcome these difficulties, this paper proposes a prototype decision support model named CRAS-CBR using case based reasoning (CBR) to support auditors in making their professional judgment on the assessment of the level of control risk of the general accounting system in the manufacturing industry. To validate the performance, we compare our proposed model with benchmark performances in terms of classification accuracy for the level of control risk. Our experimental results showed CRAS-CBR outperforms a statistical model (MDA) and staff auditor performance in average hit ratio.

Keywords:

Case-Based Reasoning, Internal Control Risk Assessment, Analytic Hierarchy Process, Audit Expert Systems, Risk-Based Audit Approach

1. Introduction

Independent auditors perform financial statements audits to determine whether the financial statements of a company are fairly stated in accordance with the generally accepted accounting principles. When performing a financial statements audit, auditors are required to comply with the Generally Accepted Auditing Standards (GAAS). GAAS has been developed based on practical experiences. Accordingly, when changes occur in the business and audit environment, GAAS has been changed and amended as well.

Information Technology (IT) and the internet have been major drivers for changes in all aspects of the business processes and activities, and thus have brought major changes to the audit environment as well.

For the accounting and information system adopting advanced IT, such as the distributed processing based on the client/server computing, networking, and open system architecture, the level of control risk has generally been increased. As a result, the overall audit risk has also been increased. Accordingly, auditors are required to apply enhanced audit approaches equipped with extended IT knowledge.

In addition, the internal controls adopted under the non-computerized environment have become less effective to prevent or detect errors on a timely basis for the accounting system adopting advanced IT. As a result, from management's perspective, new valid internal control tools and procedures have been developed and adopted. From the auditors' perspective, a modified internal control framework has been required to properly classify internal controls into several different groups based on their implications on efficient and effective audit procedures under an advanced IT environment.

It has also become necessary to apply different test techniques and tools. Under an advanced IT environment, most transactions are processed by the programmed procedures and the related data and evidences are stored in an electronic form. The audit test tools and techniques applied for a traditional accounting system become not applicable, nor efficient. Auditors should develop new test tools and techniques preferably using IT, including audit software, IT security assessment tools, etc.

GAAS has been revised considering these changes in the audit environment, thus new SAS's including SAS No. 55, No. 78, and No. 94 have been issued. To determine the timing, nature and scope of the substantive test, it is required to assess the level of control risk as one of "high", "medium", or "low". In practice, however, this decision is made not based on objective rules or criteria, but rather is based on professional judgment and experience, thus under-experienced auditors have difficulties to successfully make this assessment decision.

Case-Based Reasoning (CBR) is a problem solving paradigm which is preferably used where the domain rules are incomplete, ill-defined, and inconsistent (Ashley & Rissland, 1987).

In this regard, the purposes of this research is to develop a prototype decision support model named CRAS-CBR using CBR to facilitate auditors in making their professional judgment relating to the assessment of the level of control risk of a general accounting system in the manufacturing industry.

The remainder of this paper is organized as follows. The next section, as research background, describes current risk-based audit approach and internal control assessment, and the applicability of CBR thereto. In Section 3, we propose the CBR model, CRAS-CBR, to support the assessment decision of the level of control risk. Section 4 shows experimental analysis and results using CRAS-CBR. Finally, the conclusions, limitations and future research directions are described in Section 5.

2. Research Background

2.1. Risk-Based Audit Approach and Control Risk Assessment

In an audit environment where transactions are processed through computerized programmed procedures, the isolated error rate measured on a sampling basis becomes less useful. Instead, the systematic errors of programmed procedures and the level of control risk underlying in the computerized system become more useful to determine the nature, timing, and scope of substantive tests. Mainly due to this recognition, there has been a change in the audit approach from "compliance test based audit approach" to "risk-based audit approach". SAS No.47, Audit Risk and Materiality in Conducting an Audit, conceptually defines the risk-based audit approach. SAS No.55, Consideration of the Internal Control Structure in a Financial Statement Audit, superseding SAS No.1, procedurally details the risk-based audit, which is subsequently amended by SAS No.78 and SAS No.94.

SAS No.47 defines audit risk as "the risk that the auditor may unknowingly fail to appropriately modify his or her opinion on financial statements that are materially misstated." This audit risk has three major components: inherent risk, control risk, and detection risk. Inherent risk is "the susceptibility of an assertion to a material misstatement assuming there are no related internal control structure policies or procedures"; Control risk is "the risk that a material misstatement that could occur in an assertion will not be prevented or detected on a timely basis by the entity's internal control structure policies or procedures"; Detection risk is "the risk that the auditor will not detect a material misstatement that exists in an assertion."

SAS No.55 redefines the three elements of an internal control structure as the control environment, the accounting system, and the control procedures. These elements should be considered in assessing the level of control risk, according to which the acceptable level of the detection risk is determined, and accordingly the auditor may alter the nature, timing, and extent of the substantive test.

Subsequently, the Committee of the Sponsoring Organizations (COSO) of the Treadway Commission (1992) issued a report named "Internal Control - Integrated Framework", which newly defines internal control and its components in a broader and more comprehensive perspective. Following the COSO Report, SAS No.78 was issued and partly modified SAS No.55., which has been amended again recently by SAS No.94.

Auditors have incorporated the newly issued SASs and the newly defined internal control in their audit practices. The overview of audit approaches currently adopted by PricewaterhouseCoopers, one of the Big 4 accounting firms, is as follows:

"Initial audit activities", the first step, identify the terms and requirements of the audit, audit acceptance, allowing resources, staffing and such. "Understand business and industry" is the second step where the auditor reviews the organization and its industry; prior years' audit results; recent financial information; applicable accounting, auditing, and regulatory standards. The auditor also uses this information to identify inherent risks. "Understand the internal control structure and its audit implications" is the third step. This includes the preliminary assessment of the control environment, information systems and computer environment, and monitoring controls. Next, is to "prepare audit testing plan". At this point, the auditor reviews the information gathered in the previous steps, and makes decisions about audit strategy and the resulting test plan. There are three audit strategy options: no control reliance, some control reliance, and high control reliance

If reliance can not be placed on application and general computer controls or monitoring controls, or if it is not efficient to do so, a no control reliance approach should be used. This approach will consist almost entirely of substantive tests. If reliance can not be placed on the application and general computer controls but the client has strong monitoring controls, some control reliance approach should be used. This approach will consist of a combination of tests of monitoring controls and substantive tests. The extent, but generally not the nature, of the substantive tests can be reduced. A high control reliance approach should be used if reliance can be placed on the application and general computer controls as well as the monitoring controls. This approach is generally the most efficient approach because control testing is generally less costly and less time consuming than substantive testing.

In order to determine one of the three options, the level of control risk should be preliminarily assessed as either one of "maximum", "below maximum" or "low".

The next step is to perform the substantive tests according to the audit testing plan. In the case of no control reliance, the extended substantive test is to be performed. In the case of some control reliance case, the regular substantive test is to be performed. In the case of high control reliance, the reduced substantive test is to be performed. The last step is to finalize the audit, i.e., to develop the audit report, depending on the requirements of the particular audit.

The approaches described above are summarized in Figure 1.

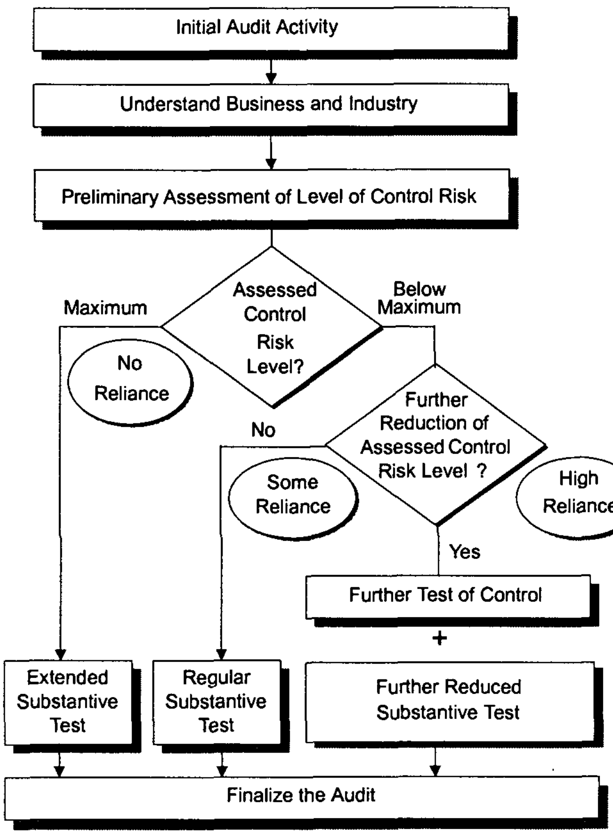

Figure 1 - Risk-based Audit Approach

When applying audit approaches as summarized above, however, it is practically difficult to establish objective rules or criteria to differentiate among "maximum", "below maximum", and "low" level of control risk. In practice, the judgment for this differentiation is made based on the auditors' professional judgment and experience. Accordingly, it is difficult for the under-experienced auditors to make this decision effectively.

To support the auditors to make this assessment decision, a prototype decision support model using the CBR is proposed in this study, considering the fact CBR is preferably used where the domain rules are incomplete.

2.2. Case-Based Reasoning (CBR) for Audit Decision Making

An expert system employs human knowledge captured in a computer to solve problems which require human expertise. It imitates the reasoning processes experts use to solve specific problems. Such systems can be used by non-experts to improve their problem-solving capabilities and also by experts as knowledgeable assistants.

CBR is a problem solving paradigm to apply an analogical reasoning approach to practical problems by adapting solutions which were used to solve old problems and to use them for solving new problems. Instead of relying solely on general knowledge of a problem domain, or making associations along generalized relationships between problem descriptors and conclusions, CBR is able to utilize the specific knowledge of previously experienced, concrete cases. Another important difference is CBR is also an approach to incremental, sustained learning, since a new experience is retained each time a problem has been solved, making it immediately available for future problems. In particular, CBR is often used in task domains which have no strong theoretical model and where the domain rules are incomplete, ill-defined, and inconsistent (Ashley & Rissland, 1987).

As it is difficult in auditing to establish a clear rule when making professional judgment in various steps, CBR has been welcomed for consideration in establishing and supporting audit practices. SCAN is an CBR model for generating information system control recommendation for internal auditors (Morris, 1994). Lee and Han (1998) developed a prototype CBR system, EDICBR for generating EDI controls recommendations.

The central tasks which CBR methods have to deal with are to identify the current problem situation, find a past case similar to the new one, use that case to suggest a solution to the current problem, evaluate the proposed solution and update the system by learning from this experience (Kolodner, 1991,1993; Riesbeck & Schank, 1989; Slade, 1991). Figure 2 illustrates the processes involved in CBR represented by a schematic cycle. There are five steps in CBR: introduction of a new problem, retrieval of the most similar cases, adaptation of the most similar solutions, validation of the current solution, and system learning by adding the verified solution to the database of cases.

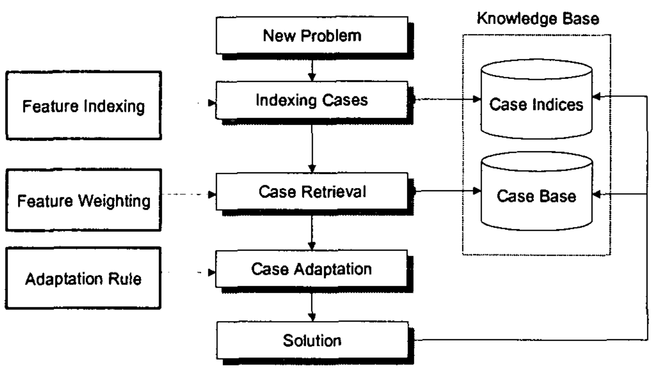

Figure 2 - Overview of the Case-Based Reasoning Process

CBR is preferred over rule-based systems if rules are inadequate to express the richness of the domain knowledge

Brown and Gupta (1994) states CBR seems the best suited for domains which are experience-rich such as legal litigation, design, planning, and diagnosis. Considering the nature of the audit domain where rules are difficult to be defined, CBR can provide a good solution to enhance the control risk assessment procedures under the current GAAS.

This study develops a prototype CBR system named CRAS-CBR, which can support auditors in making their professional judgment relating to the assessment of the level of control risk of a general accounting system in the manufacturing industry.

3. Development of CRAS-CBR

This section describes in detail our proposed development process of CRAS-CBR according to the CBR process shown in Figure 2.

3.1. Case Indexing for CRAS-CBR

Indexing cases is related to the issues of "How to represent the cases?" and "How to choose appropriate indexes?" There exist two different philosophies in selecting indexes. One is to analyze the domain and tasks then find the predictive features. A checklist-based approach supports this philosophy. The other is to choose indexes as individually as possible for each case. A explanation-based approach support this philosophy (Kolodner, 1993). In actual selection, the combination of the two approaches may be used.

Although case retrieval in CBR systems is often based on the criteria pre-selected by the system designer, a modeling index is important for both practical and cognitive reasons. A pre-defined set of indexes is unlikely to be adequate for real-world tasks. For example, poorly-understood task domains and changing circumstances in real-world situations may make it difficult to predict a priori which indexes should be used to store and retrieve cases.

In selecting the indexes for assessing the level of control risk in this study, those factors which affect the level of control risk should be identified. In order to identify those factors, the following approach is applied:

First, the integrated conceptual framework for internal control as defined by the COSO Report, and the control factors to be evaluated according to the SAS's No. 55, 78, 94, Consideration of the Internal Control Structure in a Financial Statement Audit are considered. According to COSO, internal control consists of five interrelated components: control environment, risk assessment, control activities, information and communication, and monitoring. The control environment is a function of the governance structure, integrity and competence of an organization's people, senior management's operating style and philosophy, and the extent to which employees understand they will be held accountable for their actions. Risk assessment is the identification and analysis of the risks as related to the achievement of objectives. Control activities ensure necessary actions be taken to address risks. There is a range and variety of specific control activities which employees perform every day. Under IT environment, control activities are classified into general computer control and application control. Major aspects of information and communication include information systems, communication of control responsibilities, organizational communication, and external communication. Monitoring control is the ongoing process to ensure that internal controls are functioning as intended. This is important because as internal and external factors change, once-appropriate and effective controls may no longer be adequate. These internal control components are the basic sources of reference to identify the factors that determine the level of control risk of a company.

Secondly, the checklists currently used in practice by auditors for the preliminary assessment of the level of control risk under the most recent audit approach are reviewed, for which the TeamAsset version of year 2001 is referred. TeamAsset is an audit toolkit developed in accordance with the SAS's and used by PricewaterhouseCoopers. It is updated annually according to the changed audit environment and audit approach. To preliminary assess the control risk level in practice, control environment, risk assessment procedures, information and communication environment, and monitoring controls are evaluated. Control activities will be further tested to obtain more evidences in case of high reliance approach. The checklists in TeamAsset referred to for this research purpose include; Section 200 (Control Environment), Section 600 (Information about Systems and Computer Environment), and Section 800 (Monitoring Controls).

Thirdly, experts who have engaged in auditing practices for more than 10 years are interviewed and their opinion is additionally considered, especially for determining the weight of each factor in assessing the overall level of the control risk.

Based on the above-mentioned approaches, the factors affecting the preliminary judgment of the level of control risk are identified into three groups as "Inherent Risks Factors", "Control Environment Factors", and "System and IT Environment and Monitoring Factors". As inherent risks are basically related to the industry, and this research is already limited within the manufacturing industry, our indexing for CRAS-CBR is focused on the second and third factor groups.

An understanding of the control environment is essential for the preliminary assessment of the level of control risk of a system. The control environment represents the control atmosphere for the entity and is the foundation for other components. The system and IT environmental and monitoring factors are those which determine the general conditions for individual application control and general computer control.

These two factor groups are further broken down into six factor categories as independent variables used in our model as shown in Figure 3.

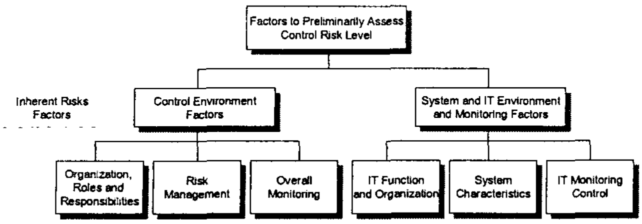

Figure 3 - Index Structure of Cases for Control Risk Assessment

According to the TeamAsset classification, "Control Environment" and "Risk Assessment" factors under the COSO are grouped into "Control Environment Factors" group as "Organization, Roles and Responsibilities" and "Risk Management" respectively, and "Monitoring" factor under the COSO is divided into "Overall Monitoring" and "IT Monitoring Control" based on the IT-relatedness then grouped into "Control Environment Factors" group and "System and IT Environment and Monitoring Factors" group, respectively.

These six factor categories are further broken down into 23 factors and then into 56 index items. In summary, Figure 4 shows the 23 factors used for the preliminary assessment of the level of control risk in our study. Each index item was measured on a five-point Likert-type scale for the preliminary assessment of the level of control risk.

1. Control Environment Factors
(1). Organization, Roles and Responsibilities
- Role of the Board of Directors
- Effectiveness of the Organization and Key Management
- Human Resource Policies and Procedures

(2) Risk Management
- Management' s Risk Assessment Process
- Awareness of Compliance with Laws and Regulations

(3). Overall Monitoring
- Reasonableness of Management' s Plans and Budgetary Controls
- Reliability of Financial Reporting and Management's Estimates
- Role of the Audit Committee and Internal Audit

2. Systems and IT Environment and Monitoring Factors
(4). IT Function and Organization
- IT Strategy
- Management and User Satisfaction
- IT Organization
- IT People

(5). System Characteristics
- Technical Architecture
- Usage of Emerging Technologies
- Key Application Background (General Accounting)
- Significant Changes to System and IT Environment
- Known Problems with Systems

(6). IT Monitoring Control
- IT Performance Measures
- System Development and Implementation
- Application Maintenance
- IT Security
- Computer Operation
- Business Continuity and Disaster Recovery Plan

Figure 4 - Risk Factors

The dependent variable in our study is defined as low, below maximum, and maximum control risk. Table 1 shows that each control risk represents its control effectiveness and control condition.

Table 1 - Assessment of Control Effectiveness and Control Risk (Hitzig and Jacoby, 1995)

Control Effectiveness	Control Condition	Assessed Control Risk
Highly effective	Controls exist. No deviations disclosed in tests of controls.	Low
Moderately effective	Controls exist. Deviations detected, but unlikely to exceed tolerable rate.	Below Maximum
Not effective	a) Key controls absent. b) Controls exist. Deviations detected, but with a high risk of exceeding tolerable rate.	Maximum

Table 2 - Reliability Test of Internal Control Factor Categories

Internal Control Factor Categories	Cronbach's Alpha
(1) Organization, Roles and Responsibilities	0.8995
(2) Risk Management	0.8508
(3) Overall Monitoring	0.8809
(4) IT Function and Organization	0.8517
(5) System Characteristics	0.8995
(6) IT Monitoring Control	0.9406

This study uses a questionnaire method to measure the independence variables used in our models. Then, to discern the underlying constructs in the 56 index items, a principal components factor analysis with varimax rotation is performed. Reliability tests are conducted for each factor category consisting of more than one item. Reliability is the stability of the scale based on an assessment of internal consistency measuring the construct for the collected data. Relationships among the items in each factor category were examined to determine whether they measured the same concept. Cronbach's alpha is the most popular reliability coefficient in social science research; it involves computing the average of correlations among responses to all possible pairs of items (Cronbach, 1951). The coefficient alphas of research variables are indicated in Table 2. All scales exhibited sufficient reliability, as they exceeded the reliability guidelines of 0.7 (Nunnally, 1978) after deleting low-to-total correlated items.

3.2. Case Retrieval

The purpose of case retrieval is to select and retrieve from the case memory the cases which best serve problem solving (Xia & Rao, 1999). There are three main approaches to using indexes to retrieve cases: nearest neighbor, inductive reasoning, and knowledge-guided indexing (Barletta, 1991). Depending on the complexity of the domain, one or all the above three indexing mechanisms may be used to select and retrieve appropriate cases.

In addition, the organizational structure of the indexes in order to retrieve efficiently the most similar case is another important issue. Different organization structures of case indexes give rise to different algorithms for retrieving them (Kolodner, 1993). A number of different organizational structure of indexes have been developed: flat memory, shared feature networks, prioritized discrimination networks, redundant discrimination networks, and inductive networks (Hansen *et al.*, 1995).

Inherent risk factors provide conditioning effect on other control risk factors in terms of their impact on determining the level of control risk. It is generally understood that inherent risks are different by industry. As this paper is focused only on the manufacturing industry, the case retrieving criteria are focused on the control risk factors other than the inherent risk factors as follows.

For each control risk factor index item, a case is scored based on the five-scale measurement. The difference score for each index item between the new and existing case is calculated and added up by multiplying the respective weight (See Function (1)).

The case retrieving criteria is to select the most similar case to the new case, out of the case base. The similarity criterion follows Euclidean distance function. As a result of case retrieval step, the most similar case to the new case is identified.

In general, the Euclidean distance metric of attribute-weighted k-NN (EDWKNN) is

$$EDWKNN\left(n,o^k\right)=\sqrt{\frac{\sum_{i=1}^{m} w_i\times\left(n_i-o_i^k\right)^2}{\sum_{i=1}^{m} w_i}} \qquad (1)$$

n_i is the ith attribute of the new case;
o_i^k is the ith attribute of the kth candidate old case.
w_i is the relative importance of the ith attribute for each case

As shown in Function (1), a global similarity measure EDWKNN between two cases n and o can be a weighted sum of local similarity measures S between the m attributes that make up the cases. The weights wi evaluate the relative importance of the attributes for each class.

Basic nearest neighbor classifier uses the nearest neighbor (1-NN) to determine the class label of an unseen case in the test set. However, an extension of basic nearest neighbor classifiers uses k nearest neighbors instead of only the nearest neighbor to determine the class label of an unseen case in the test set. This study uses 1-nearest neighbor in case retrieving.

3.3. Analytic Hierarchy Process (AHP) Approach for Feature Weighting

One of the main challenges in developing k-NN algorithms are feature weighting (Aha, 1998). The purpose of a feature weight mechanism is to give low weight to features which provide little information for classification (e.g., very noisy or irrelevant features) and to give high weight to features that provide reliable information.

Conventional k-NN algorithms treat each attribute as equally important in classification. However, the importance weighting of each attribute directly affects the accuracy of classification. Several researchers have reported benefits from using domain-specific information to assign feature weights. This is commonly done in CBR applications (e.g., Shimazu et al., 1994). Domain-specific knowledge can usefully guide transformations of the sample space.

One way to assign importance values is to have a human expert assign them as the case library is being built. The expert might have knowledge about which dimensions and combinations of dimensions make good predictors (Kolodner, 1993; Cognitive Systems, 1992).

Another way to assign importance values is to do a statistical evaluation of a known cases to determine which dimensions predict different outcomes and/or solutions best Those which are good predictors are then assigned higher importance for matching. If there is little domain knowledge for attribute weighting, it is more effective in terms of time and statistically more accurate to determine automatically the attribute weights by a data-driven approach in a reasonably short period of time (Wettschereck & Dietterich, 1995).

In this study, we use human expertise using an AHP approach to acquire domain-specific information for assigning feature weights to the Euclidean distance function.

The analytic hierarchy process (AHP) is a widely used method for analyzing complex discrete alternative decision problems with multiple qualitative criteria (Saaty, 1988). In the AHP, the decision problem is decomposed into a tree-like hierarchical structure, with the overall goal at the top and the discrete alternatives at the bottom. The intermediate levels of the hierarchy represent lower level criteria which contribute to the overall goal. The AHP is designed to cope with both the rational and the intuitive when evaluating a number of alternatives based on multiple criteria. In this process the decision-maker carries out only pairwise comparative judgments which are then used to develop overall priorities for ranking the alternatives. The AHP has been applied to several auditing problems (Arrington *et al.*, 1984; Bagranoff, 1989).

In this study, we use the AHP to establish the relative priorities of internal control factors as indicated by five professional auditors with more than 10 years of experiences. The five experts were asked to indicate the relative importance of the six internal control factor categories. This process is used to develop CBR with relative feature weighting.

Table 3 - Individual's and Group's Feature Weighting Using AHP

Variable	Auditor1	Auditor2	Auditor3	Auditor4	Auditor5	Avg.
(1) Organization, Roles and Responsibilities	0.083	0.036	0.083	0.100	0.100	0.082
(2) Risk Management	0.083	0.107	0.083	0.100	0.100	0.101
(3) Overall Monitoring	0.083	0.107	0.083	0.300	0.300	0.157
(4) IT Function and Organization	0.250	0.079	0.150	0.052	0.052	0.103
(5) System Characteristics	0.250	0.194	0.150	0.129	0.129	0.177
(6) IT Monitoring Control	0.250	0.478	0.450	0.318	0.318	0.380
(Consistency Ratio)	(0.0)	(0.03)	(0.0)	(0.02)	(0.02)	

The pairwise comparisons were used to construct three matrices which were used to compute weights which measure: (1) the relative importance of each control factor category within each of the two control factor group; and, (2) the relative importance of each factor group to the overall goal of preliminary assessment of internal control risk level.

Table 3 summarizes the average results of the individual AHP judgment models for the 5 respondents in terms of the mean weights of the synthesized (aggregated) models, and the percent frequency with which control categories and elements were judged.

The overall consistency ratio is also calculated for each respondent and indicated in Table 3. This process provides for the calculation by considering the consistency of judgments entered versus a calculation of consistency for random judgments. For example, a high level of inconsistency indicates decision maker fatigue or judgments that have not been well thought not. An inconsistency index of greater than 0.1 suggests that the decision maker should reconsider some responses.

3.4. Case Adaptation

The case adaptation process is to modify the solution as suggested by the retrieved case, to suit and meet the requirements of the new case. There are two kinds of adaptation: (1) structural adaptation, where adaptation rules are applied directly to the solution retrieved from the most similar case: and (2) derivational adaptation, where rules which generated the original solution are rerun to generate a new solution appropriate to the new case. This means parts of the retrieved solution are re-executed, rather than modified directly,

Case adaptation can be system-driven or user-driven. If no sufficiently similar cases are found in the case base, then the user has to help in the adaptation process. If a CBR system finds a relevant case, the system tests the solution to decide if the case needs to be adapted to the current problem or if it can be used as it is. If the case can be used as it is, then the solution to the past case becomes the solution to the current problem. The solution is then evaluated, debugged, and if valid, presented to the user. The system then learns about the new case. If the solution is unacceptable, the problem-solving process is reinitiated.

In this study, the assessed level of control risk and the corresponding subsequent audit tests performed for the most similar case retrieved are suggested to adopt for the new case.

4. Experimental Analysis and Results Using CRAS-CBR

Evaluating a CBR system is a difficult task, due to the subjectivity of expertise. As a result of the difficulties, CBR systems are evaluated in less formal and more experimental ways. The principal judge of the system's quality is the domain expert, who can tell if the results are satisfactory. Potential users can also serve as judges in regard to ease of use, comfortable interface, and clarity of explanations. A common method to evaluate the quality of a CBR system is to compare its performance with an accepted criterion, such as a human expert's decision. Reduction of time needed to perform existing tasks without reduction in quality can also be a good initial criterion for evaluation of a CBR system.

In order to validate the performance of CRAS-CBR, 137 Korean companies' cases are collected and indexed out of the actual audit cases for the manufacturing industry for the year 1999. Using these cases, we analyze the performance of CRAS-CBR for the internal control risk assessment and this performance is compared with our benchmark performances i.e., the multiple discriminant analysis (MDA) performance and staff auditor performance.

The comparison with staff auditor performance is considered to evaluate the minimum usefulness of CRAS-CBR in practice. To measure the staff auditor performance, 5 staff auditors who passed CPA examination in Korea were asked to assess the level of control risk for each case. The mode of five auditors' assessments for each case is used to calculate the hit ratio.

Due to the difficulty in collecting a large set of internal control risk assessment cases, this study adopts the k-fold cross-validation method for the comparison of model performance. This method reduces the possible bias which might be caused by a small sample. The average classification accuracy of each performance of CRAS-CBR, MDA and staff auditor across 10 holdout sets is presented in Table 4.

Table 4 illustrates that our proposed model has better performance than MDA and staff auditor in average hit ratio.

Table 4- Summary of Validation Results (Unit: Hit ratio, %)

Set	Staff Auditor	MDA	CRAS-CBR
1	80.0	93.3	80.0
2	100.0	80.0	93.3
3	100.0	86.7	93.3
4	86.7	86.7	100.0
5	92.3	100.0	100.0
6	100.0	84.6	92.3
7	76.9	90.3	100.0
8	69.2	84.6	84.6
9	69.2	84.6	84.6
10	58.3	75.0	75.0
Avg.	83.9	86.6	90.3

Furthermore, we use the difference test between two proportions to examine whether the predictive performance of our proposed model is significantly higher than that of MDA and staff auditor. The p-level of the difference test is computed based on the t-value for the respective comparison. Table 5 shows the result of the difference test and that our proposed model performs significantly better than staff auditor at a 10% level but does not perform significantly better than MDA.

Table 5 - Difference Test between two Proportions for the Comparison of Performance between Models (Unit: p-level)

	MDA	CRAS-CBR
Staff Auditor	0.2407	0.0705(*)
MDA	-	0.2185

*: significant at 10 %

5. Conclusion

This study developed a prototype system using CBR named CRAS-CBR to support auditors in making their assessment of the level of control risk under current audit procedures. The CRAS-CBR proposed in our study was designed for the manufacturing industry and covers only the general accounting system.

The CRAS-CBR development process is as follows. First, cases were indexed based on the factors affecting the preliminary judgment of the level of control risk, which are classified into two groups: 1) control environment factors and 2) system and IT environment and monitoring factors. These factor groups are further classified into six internal control factor categories, three for control environment and the other three for system and IT environment and monitoring. Second, the AHP was used to establish the relative priorities of the six internal control factor categories as indicated by five professional auditors. Third, the priorities of the factor categories were used in retrieving the most similar case and the assessed level of control risk for the retrieved case is to be adopted to the new case. Finally, to validate the performance of CRAS-CBR, its performance is compared with that of MDA and staff auditors. The experimental results showed our CRAS-CBR model has better performance than MDA and staff auditors by an average hit ratio of approximately 3.7% point and 6.4% point, respectively. In addition, this result gives a possible implication that CRAS-CBR can be used as a supporting tool for the staff auditors to enhance their performance.

However, this study has the following limitation. Even though the average hit ratio of our model was better than that of MDA and staff auditors, our experiment depends on a small size of sample. Therefore, these results should realistically be viewed as only an indicator of the plausibility of this approach. Furthermore, if the sample size is expanded, future work will be able to find more generalizable results.

In addition, the usefulness of CRAS-CBR can be further enhanced to satisfy following needs, if additional relevant indexes and retrieving algorithms can be incorporated:

- To develop substantive tests as more tailored to the case, if the case is indexed to provide more information about the adopted substantive tests

- To develop recommendations how to reduce the control risk level, i.e., how to improve the internal control

This system can be extended to cover other transaction types and other industries. When considering extension to cover other transaction type, new cases can be developed using the same index structure, i.e., the same indexes and weights. When collecting case data for other transaction type within the same company, it is expected to require different index data for "System Characteristics", while the data for other indexes remain as the same. When considering extension to cover other industries, the same indexes can be used as a starting point. However, the weights of each index items can be different by industry to reflect its own inherent risk. The same procedures applied in this paper, i.e., AHP and etc. can be adopted to determine the index weights for other industries.

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