Artificial Intelligence in Accounting and Auditing: Towards New Paradigms, Volume 4

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Introduction

Artificial Intelligence in Accounting and Auditing: Towards New Paradigms

Miklos A. Vasarhelyi and Alexander Kogan

This is the fourth volume of the AI & ES in Accounting and Auditing series. It encompasses fifteen articles, including this introduction, all original manuscripts, unlike the previous volumes which had a few reprints. The first volume was published in 1989, when AI/ES in Accounting was a new paradigm, and detractors claimed in not to be applicable to accounting and finance. Volumes 2 and 3 were published in 1994, and there was concern for the applicability of the paradigm in practice, and on the usage of the tools on a day to day basis. Three years are passed and the field has matured to acceptability and self-evaluations. A series of new technologies, akin or integral to AI/ES started to be used and are being progressively incorporated into the state-of-the-art. Soul searching and evaluation is progressing in the academic field to assess the emerging tools and where is the optimum domain of their applicability.

CPA firms continue slowly to use the technology both in internal audit matters as well as a tool for consulting and other services. International usage blossomed and for the first time we include an international-focused survey (Sanchez Tomas) and two internationally focused applications (Back et. and Sangster). The Sanchez Tomas article presents a rich bibliography with many international pieces, in particular from France and Spain.

The book is divided into five parts: the **first** encompasses two surveys of the literature that position the current state-of-the-art of the field. The **second** part of the book focuses on the maturing neural net paradigm. The **third** part of the book has two articles focusing on international applications. The Back et al article is placed in the third part of the book but also belongs to the merging neural network paradigm. The fourth part of the book focuses on audit applications, and the **fifth** part is a methodological section showing new focuses and methods that are progressively emerging and surrounding the field.

Following this introduction we present in Part I two surveys studies with some degree of overlap. The Sanchez study links several international studies to the literature.. The domain is divided into: expert systems in accounting, expert systems in auditing, expert systems in cost and management accounting, expert system applications in the financial accounting domain, expert systems for financial statement analysis and
expert systems in financial planning and in financial analysis

The Yang & Vasarhelyi paper summarizes the current application of expert systems in accounting. The areas of emphasis covered are: (a) Auditing, (b) Taxation, (c) Financial Accounting, (d) Personal Financial Planning, and (e) Management Accounting. The focus is mainly on US research and applications.

Part II presents two papers using the neural network paradigm. The Back et. al. paper of the ensuing part can also be considering using this paradigm. The Cheh, Weinberg, and Yook paper examines the efficacy of the neural technology as an investment expert system and proposes a framework for evaluation. The O'Callaghan, Walker and Sale explores the differences between neural network and auditor assessments of internal control. The research uses the Committee of Sponsoring Organizations Integrated Framework for Internal Controls (COSO) as a basis for studying assessments of internal controls, in particular the resulting under and over reliance on internal controls.

Part III focuses on International applications with the Back et. Al. paper, and the Sangster paper. It should also be noted that the Sanchez paper also falls in this category but is mainly a survey. Back, lrjala, Sere & Vanharanta investigate the potential of neural networks for pre-processing data for competitive benchmarking. The study demonstrates how a large annual reports database on international pulp and paper companies can be pre-processed, i.e. classified with self-organizing maps that is one form of neural networks. The test results are encouraging, and

show that self-organizing maps are a viable tool for organizing large databases into clusters of companies having similar financial characteristics.

The Sangster piece, examines the fact that faced with a widely diverse range of customers seeking finance for ventures of varying complexities and profiles, and a high level of losses as the result of defaulting borrowers, the need for an effective means of assessing commercial risk has become a major concern for banks. The paper describes the background to the need for commercial risk assessment, considers the relevance of financial ratio-based quantitative decision support models, and reports the development and structure of COMPASS, the Bank of Scotland's commercial risk assessment expert system, that has succeeded in capturing and modeling the inherent risk of the Bank of Scotland's lending process.

Part IV has four papers focusing on audit related issues. The Baldwin-Morgan paper attempts a comprehensive discussion of the applicability of expert systems to auditing and the impacts of expert systems on audit firms. The article interprets the environment of auditing and its readiness for expert systems development, illustrates the applicability of expert systems to a broad range of tasks associated with an independent audit of financial statements, and recounts the impacts of expert systems used for audit tasks.

The Dillard & Yuthas paper discusses issues of ethics vis-à-vis expert systems. The ethical issues raised with respect to expert systems (ES) are a microcosm of those to be addressed concerning the application of technology, especially computer technology. Previous research has focused on a limited subset of the ethical issues surrounding the development and use of audit ES. The issues subset must be expanded if the ethical implications surrounding ES are to be meaningfully addressed. Niebuhr's (1963) cathekontic ethics is enlisted to articulate more clearly the context within which audit expert systems are developed and implemented. Discourse ethics is then proposed as a way of exploring, and possibility resolving, ethical dilemmas. The integration of these two ethical structures at least partially transcends the dichotomies of teleological and deontological ethical theories that have been employed to date.

The Greenstein and Baldwin-Morgan paper describes the importance of the audit client engagement decision, the application of expert systems to that process as an example of audit process reengineering, a proposed expert system (ACE) to support audit client engagement decisions, the potential impacts of such a system, and the future of expert systems use as an audit process reengineering tool.

Part V brings together a series of diverse papers that illustrate the merging paradigms surrounding expert systems. Chen, McLeod, & O'Leary examine the need for the evolution of accounting databases. It postulates that it is necessary to evolve accounting databases that are structured based on resources, events and agents (REA), as is the case with all such enterprise models. The paper presents one approach to aid in the evolution of accounting databases. A number of “evolution” events are elicited as part of that evolution process. The actual tasks necessary to evolve those databases in through those events are summarized in SEAtool, a prototype system designed to assist in the evolution of REA accounting database systems.

McEacharn and Zebda discuss the usage of fuzzy logic in expert system research...Many of the problems faced by accountants and auditors are ill-defined and unstructured, problems which are especially well-suited for expert system application. The paper briefly describes the expert system environment within accounting and auditing, illustrate a major criticism in the design of these systems, and introduce a potential solution to the weakness.

McKee illustrate a trend in the literature where algorithms and methods are beginning to be developed as opposed to being imported from other fields. It extend a prior bankruptcy study by testing the model on a different sample of 202 public companies The results are improved and the question is raised: Was the change in model performance due to the variables employed or to the classification points selected for the variables?” A recursive partitioning algorithm ID3 is used to recalculate optimum classification points for the 202 company sample. This results in a second model using the same two ratios as the original model but employing a different classification rule and points. This research indicates that ID3 has been used to develop a robust bankruptcy prediction model that is simple and consistent with the temporal continuity theory.

Swigger, Michaelsen and Trewin describe the development of an intelligent tool to enable tax specialists to manage and use data more effectively. An intelligent interface was developed for a tax data base, i.e., LEXIS. The interface

was developed for two limited domains of expertise, i.e., worthless stock and casualty losses. The interface used an artificial intelligence technique that is similar to those used for acquiring knowledge from experts. This technique was used with the data base interface to facilitate access to tax information by tax students with little or no experience with a data base query language. The interface was developed to solve a critical interface problem existing between end-users and data bases: the difference between how users perceive the data and how the data is actually stored. The interface elicits information from the human user and then constructs and analyzes that knowledge with respect to the user's information needs and the data base being used. The interface creates a user 'model' of the information to be used in resolving ambiguities between the end-user's perception of the information and the computer's method of organizing the information.

In conclusion, Volume 4 of the series presents a series of original research studies of a more mature discipline, that now uses a series of complementary tools, drawn from many disciplines, to create / propose and enhance our ability to function intelligently. Two surveys show a growing field of research, rich in practical applications in all domains of accounting. Neural networks are now a major component of the area and are progressively being applied to more and more domains of knowledge. Studies are now dispersed among the different disciplines of accounting and international hubs are rapidly developing. Issues of computer sciences (interface design, databases), mathematics (computational algorithms) and statistics (fuzzy sets) merge to expand horizons and to flow towards new paradigms.

Miklos A. Vasarhelyi and Alexander Kogan,
Newark, January 1997

Part I: Surveys

Expert Systems Applications In Accounting

Antonio Sánchez Tomás

Introduction

Great changes have occurred in the organizational environment as an effect of the advances yielded by new production, information and communication technologies. In this new complex and changing environment, it is necessary to have available sufficient, updated and suitable information, in any moment, in order to make decisions in an effective manner. Today this is only possible using *electronic computers* and means provided by *information technology* (Sánchez 1991a, 1992a). Furthermore, due to the research undertaken in *artificial intelligence* developing *knowledge-based systems* and *expert systems*, great changes have been also produced in knowledge management, being this an essential element for decision making.

In this paper we study the above mentioned systems from the accounting point of view. Through this study we show an integrated view of applying expert systems to the accounting domain. For this purpose expert systems are studied in different accounting domains. In each of these domains, the main features are indicated and an abstract of some of the main applications developed is presented.

Expert systems are computer software which contain the knowledge of an expert and mimic his reasoning processes when solving problems in a certain domain. *Expert systems* are a special subset within *knowledge-based systems*, which embody the knowledge of an expert in the system knowledge base. A formal definition for expert systems accepted by many authors is one approved by the British Computer Society Specialist Group on Expert System. This group defines an expert system as: "An expert system is regarded as the embodiment within a computer of a knowledge-based component, from an expert skill, in such a form that the system can offer intelligent advice or take an intelligent decision about a processing function. A desirable additional characteristic, which many would consider fundamental, is the capability of the system, on demand, to justify its own line of reasoning in a manner directly intelligible to the inquirer...".(Connell, 1987, p. 221; Prado, 1991, p. 443).

Expert systems can also be defined according to its performing characteristics. To this effect, Hayes-Roth (1984, p. 51) considered that main characteristics of expert systems are:

(1) they can solve very difficult problems as well as or better than human experts;

(2) they reason heuristically, using what experts consider to be effective rules of thumb and they interact with humans in appropriate ways, including natural language;

(3) they manipulate and reason about symbolic descriptions;

(4) they can function with data which contains errors, using uncertain judgmental rules;

(5) they can contemplate multiple, competing hypotheses simultaneously;

(6) they can explain why they are asking a question;

(7) they can justify their conclusions.

Expert Systems In Accounting

Expert systems have been successfully applied to several fields: medicine, geology, chemistry, engineering, etc. (Waterman, 1986; Harmon and King, 1988; Rauch-Hindin, 1989), in order to perform very different tasks (e.g.,

interpretation, forecasting, diagnosis, design, planning, training, control, etc.) (Hayes-Roth et al., 1983, pp. 13-16; Waterman, 1986, p. 33). Clerical, financial and accounting tasks are also fields to which expert systems can be applied. These encompass many of the requirements necessary in order to develop an expert system (i.e., they require specialized knowledge, there are real domain experts, experts are scarce, expertise needs to be recovered from different locations, most tasks require heuristic solutions,...) (Waterman, 1986, pp. 127-134). However, not in every task performed in accounting and financing it is necessary to use expert systems. So, in well-structured accounting tasks that result very mechanical and can be expressed algorithmically (e.g., financial statement preparation, ratio assessing, sampling, mailing list, ...) it is possible, and suitable, to use *traditional computing* (e.g., ordinary software, word processing, data bases, ...); in semi-structured tasks, *decision support systems* are well suited (e.g., data sheet, file consulting systems, data analysis and screening systems, ...); thus reserving *expert systems* for ill structured tasks, because these require much expert judgment and heuristics are used to reach a fast response, and the solution field can be very wide (Sánchez, 1993e).

Briefly, expert systems can be applied in every accounting area (Montesinos, 1976; Cañibano, 1982). Nevertheless, this rating would result too extensive, and furthermore unsuitable, so we try to classify every potential application of expert systems in accounting according to these areas (Anderson and Bernard, 1986; Connell, 1987; Elliott and Kielich, 1985; Englard and Kiss, 1989; O'leary 1987a; Shim and Rice, 1988):

* **Auditing:** Materiality and risk analysis, internal control evaluation, audit planning, evidence evaluation, specific account analysis, choosing an opinion, report issuing, internal auditing, EDP auditing, etc.
* **Cost accounting and management accounting:** Cost assignment and assessment, scarce resources assignment, variance control and analysis, management planning and control, management information systems design, etc.
* **Financial accounting:** accounting regulation, accounting standards, accounting record recovery and analytical review, accounting system design, accounting entries, financial statement consolidation, etc.
* **Financial statement analysis:** financial statement wealth, financial and economic analysis, business financial estate ratio assessment and understanding, trend assessment and analysis, etc.
* **Financial planning and financial services industry:** Corporate financial planning, personal financial planning, capital budgeting, treasury management, stock exchange, insurance, banking, credit granting, etc.

Now we try to briefly analyze the expert system applying technology in each and every of these accounting areas.

Expert Systems In Auditing

General Domain Features.

Audit, due to technological change, has changed substantially. We have witnessed many changes in the profession. Among which: increasing number and complexity of auditing rules; many changes in professional ethics standards, improved quality in the audit work; increased competition among audit firms, lower audit fees; and new services offered to customers (e.g., financial and computing advice). Furthermore we have seen the development of new types of audit types (e.g., management auditing, computer audit, environmental auditing, etc.

These factors have made the auditing profession increasingly competitive. Consequently the new techniques provided by information technology and artificial intelligence have been adopted. These allowed the availability of more relevant and timely information to facilitate and accelerate the auditor's decision-making process, and hence, improve the audit quality and efficiency.

Financial audit is the "activity performed by an independent and skilled person, to analyze the economic and financial information extracted from examined accounting documents using well suited review and verification techniques. The objective is issuing a report addressed to express his opinion about the reliability of such information, in order to this information could be known by third party" (R. D. 1636/1990, Account Auditing Regulation).

The areas of audit in which expert systems can be applied are wide and diverse, including almost every audit task where audit professional judgment can be required. Expert systems in auditing applications could be classified according to these three types: (1) external audit expert systems, (2) internal audit expert systems, and (3) EDP audit

expert systems. However, because of the wide scope of the external audit field, it is worthy to create an additional sub-classification.

The audit process stages allow us to establish a rating of external audit expert systems. Jacob & Bailey (1989, pp. 157-159), based on Felix & Kinney (1982), separate the audit decision process into the following stages:

a) Orientation - The auditor gains knowledge about the client's operations and its environment and makes a preliminary assessment of risk and materiality;
b) Preliminary evaluation of internal controls;
c) Tactical planning of the audit;
d) Choosing a plan for the audit;
e) Compliance tests of controls;
f) Evaluate internal controls based on compliance test results;
g) Revision to the preliminary audit plan;
h) Choosing a revised plan for the audit;
i) Implementation of substantive tests;
j) Evaluation and aggregation of results;
k) Evidence evaluation - This could lead to further tests or form the basis of the auditor's choice of opinion;
l) Choosing an opinion which classifies the client's financial statements;
m) Audit report.

Therefore, we established a classification of expert systems in the audit domain. However, expert systems have not been developed in every taxon of this classification stage, so we group them in a sparser set as follows:

1. External audit expert systems.
   1.1. Risk and materiality.
   1.2. Internal control evaluation.
   1.3. Audit planning.
   1.4. Evidence obtaining and opinion.
   1.5. Audit report.
2. Internal audit expert systems.
3. EDP audit expert systems.

An abstract of main features of these subsets or audit functional areas can be seen in (Sánchez 1993b, 1994).

Expert system applications in the audit domain

No doubt about the accounting domain in which more expert systems have been developed is auditing. This improvement is partly due to interest and support provided by the multinational audit organizations, which have developed or funded much of the research carried out in this domain. The following is a list of some well-known expert systems:

1) SYSTEM NAME 2) REFERENCES 3) ORGANIZATION, INSTITUTION	4) SUBDOMAIN 5) APPLICATION DOMAIN 6) DEVELOPING TOOL
1) AUDITPLANNER 2) Steinbart 1987; Connell 1987; van Dijk and Williams 1990. 3) Deloitte, Haskins & Sells Foundation.	4) MATERIALITY. 5) It helps the auditors on materiality judgment in audit planning stages. The main goal in constructing this system was not only to construct a system that could solve a certain kind of problems, but to investigate on how qualitative and quantitative information affects the materiality judgments carried out by auditors. In fact it is a computational model which mimics the cognitive process of an expert reasoning on this subject. 6) EMYCIN knowledge engineering language.
1) RISK ADVISOR 2) Graham et al. 1991. 3) Coopers & Lybrand.	4) AUDIT RISK. 5) It evaluates the audit risks and also a client's economical performance. It is based on Audit Strategy Memorandum and was used by Coopers & Lybrand to identify audit risk and how to approach it. The system can be used in the audit planning stage to identify and assist to document the potential audit risks. In the final stage it can also be used to verify that every subject about the risk contained in the audit plan has been undertaken. 6) FFAST developing tool, developed by Coopers & Lybrand, ART Shell (Automate Reasoning Tool).
1)RICE (acronym for Risk Identification and Control Evaluation) 2) van Dijk and Williams 1990. 3) Arthur Andersen & Co. This system belongs to FEAP Project (Front End Analysis and Planning).	4) AUDIT RISK. 5) It assesses the risk indicators associated to a specific account to use in planning an audit commitment. The system assesses some risk indicators used to determine the error degree associated to a specific account. The information provided by the system is then used by the auditor to plan the audit commitment.
1) ARISC (Auditor Response to Identified Systems Controls). 2) 2) Meservy et al. 1986; Messier and Hansen 1987; van Dijk and Williams 1990. 3) Peat, Marwick & Mitchell Foundation, and Artificial Intelligence Research Center of Minnesota University	4) INTERNAL CONTROL. 5) It mimics the auditors' decision process in the internal control evaluation of purchasing/payable accounts/paid accounts process in manufacturing organizations, wholesale and retailing. Two specific subjects were analyzed: (1) identify the internal control system weaknesses, and (2) to suggest the specific controls to implement for compliance testing. The system was constructed intended to investigate subjects related to understanding and modeling the mental processes of the audit experts. 6) Galen Shell.
1) INTERNAL-CONTROL-ANALYZER 2) Gal 1985; Messier and Hansen 1987; van Dijk and Williams 1990. 3)	4) INTERNAL CONTROL. 5) It assists the auditor in assessing the accounting internal controls in the income cycle. The information used by the system in order to analyze the accounting internal controls is extracted from the client's source database. 6) EMYCIN Knowledge engineering language.
1) TICOM (The Internal Control Model)	4) INTERNAL CONTROL. 5) TICOM is a computer-based analytic tool which helps the

2) Bailey et al. (1983; al. 1985); Connell 1987; van Dijk and Williams 1990. 3) Peat, Marwick, Mitchell Co.	auditors to model the business internal control system, and once modeled, it allows the auditors to query the system about aspects of the resulting model, in order to assess the business internal control system. 6) PASCAL Language.
1) DECISION SUPPORT (DS) o EY/DECISION SUPPORT. 2) Broderick 1988; Murphy and Brown 1992. 3) 1º Arthur Young; 2º Ernst & Young.	4) AUDIT PLANNING. 5) It assists the auditors to prepare individual plans for each audit commitment. The system carries out audit planning and scheduling, and also indicates the weaknesses in the organizational internal control system. The system yields three types of planning documents: (1) the audit approach plan, which indicates the procedures necessary to support or reject the financial statement assertions in each account, (2) the audit schedule, that in each account details the procedures from the audit approach plan, and (3) the internal control system preliminary assessments for each data processing application labeled as significant by the auditor. 6) PASCAL Language.
1) EXPERTEST 2) van Dijk and Williams 1990; Murphy and Brown 1992. 3) Coopers & Lybrand	4) AUDIT PLANNING. 5) Produces audit schedules which include every audit aspect, or partial audit aspects about 19 standard audit schedules contained in the system knowledge base. The system also yields a report that helps the audit manager to review the audit-schedule produced. 6) Coopers & Lybrand own Shell, written in LISP language.
1) COMPAS (Computerized Planning Advisory System) 2) Murphy and Brown 1992. 3) Price Waterhouse.	4) AUDIT PLANNING. 5) It assists the auditors to select the audit procedures. The system knowledge base contains information about the procedures followed to detect every significant element in the financial statements.
1) AUDITOR 2) Dungan 1983, 1985; Connell 1987; Messier and Hansen 1987. 3) Peat, Marwick, Mitchell Co.	4) EVIDENCE OBTAINING AND OPINION DECISION. 5) It assists the external auditors to assess the adequacy of the forecasts made by the client in order to cover the bad debt risk. 6) AL/X Shell (Advice Language/X).
1) CFILE (credit file analysis) - LOAN-PROBE (enhanced late version of CFILE system). 2) Kelly et al. 1986; Willingham and Ribar 1988; Connell 1987; Messier and Hansen 1987 3) Peat, Marwick, Mitchell Co.	4) EVIDENCE OBTAINING AND OPINION DECISION. 5) It helps the auditors to evaluate the potential loss of bank loans, and also to assess the reserve necessary to cover all losses incurred in bank loan portfolio, in a bank audit context. 6) 1st INSIGHT2 Shell. 2nd NEXPERT Shell. Contains also 16 software packages written in PASCAL language.
1) EXPERTAX 2) Shpilberg, Graham, and Schatz 1986; Shpilberg and Graham 1986; Connell 1987; Messier and Hansen 1987; 3) Coopers & Lybrand.	4) EVIDENCE OBTAINING AND OPINION DECISION. 5) The system advises the auditors and tax staff accountants on the tax accrual problem and business tax planning. 6) Own shell, written in LISP language.
1) GC-X	4) EVIDENCE OBTAINING AND OPINION DECISION: THE GOING-CONCERN JUDGMENT.

2) Biggs and Selfridge 1986; Selfridge and Biggs 1988; Messier and Hansen 1987; van Dijk and Williams 1990.	5) Assists the auditors in the going concern judgments. The system works on goals and sub-goals to assess whether the business is a going concern. The GC-X carries out judgments directly from the data contained in its database, and also computes interactively with the user. 6) LISP Language.
1) AOD (Audit Opinion Decision) 2) Dillard and Mutchler 1986, 1988; Messier and Hansen 1987; van Dijk and Williams 1990. 3) Peat, Marwick, Mitchell Co.	4) EVIDENCE OBTAINING AND OPINION DECISION: THE GOING-CONCERN JUDGMENT. 5) Assists the auditors in the going concern judgment decision. 6) XINFO system.
1) CHECKGAAP 2) Connell 1987. 3) Deloitte, Haskins & Sells.	4) AUDIT REPORT. 5) Guarantees that the audit report presented by an auditor complies with the UK Companies Act. 6) BROWSE Shell. Languages C and Assembler.
1) AUDI EXPERT 2) Sierra and Bonsón 1992. 3) Univ. de Sevilla.	4) AUDIT REPORT. 5) It assists the auditor in the opinion decision and the audit report issuing. The system focuses on the reporting and conclusion compiling stages. 6) CRYSTAL Shell.
1) AUDIT MASTERPLAN (AMP) 2) Brown and Phillips 1991. 3) Institute of Internal Auditors (IIA).	4) INTERNAL AUDITING. 5) It assists the internal auditors in the audit planning.
1) EDP-XPERT 2) Hansen and Messier 1986a, 1986b; Messier and Hansen 1987; van Dijk and Williams 1990. 3) Peat, Marwick, Mitchell Co.	4) EDP AUDITING. 5) It assists the EDP auditors in assessing the audit controls of advanced computer-based systems (e.g., distributed data processing systems, database management systems, and real time and on line systems). 6) AL/X Shell (Advice Language/X).

Expert Systems In Cost Accounting and In Management Accounting

General Domain Features.

Technological changes (i.e., improved information management and disclosure, enhanced importance of information as source for decision making, new management techniques, new production technologies, ...) have also affected cost and management accounting. In the 1980's some critical voices appeared and questioned the information provided by traditional cost accounting, because it did not provide relevant and timely information for decision making (Johnson and Kaplan, 1987). This criticism, and the reactions by the profession, strengthened the role of cost and management accounting, being now considered one of the main information sources for firms.

According to the Asociación Española de Contabilidad y Administración de Empresas (AECA), cost accounting "provides analytical information related to products and services rendered by the organization, assuming the disagregation level considered proper in each situation, in order to assess the stock value, and the price of sold products and to provide this information to management, and be able to proceed to financial statement completion (AECA, 1990, pp. 21-22); while management accounting "is an accounting branch which goal is to capture, measure

and assess the internal circulation, as well as to rationalize and control it, in order to provide the organization with the relevant information for decision making" (AECA, 1990, p. 23).

The main basic goals pursued by cost accounting are (1) To assess the task, activity, and costs in the business production process, (2) to assess the cost of products and services rendered by the firm, (3) to assess the cost of sold products and to analyze the analytical results, (4) to value the production process assets in order to complete the annual financial statements.

On the other hand, management accounting, focuses mainly on the cost rationalization, planning and control process, in order to provide relevant and timely information to assist in the managerial decision making. Therefore, management accounting is a logical trend of cost accounting, because of the increasing information demands required by modern firms for decision making.

Cost and management accounting sub-domains or potential fields in which expert systems can be applied are very wide and varied. Among the most significant are: scarce resources assignment, sales and purchasing management, stock management, human resources management; work order cost assessment, management planning and control, standard costs and variance analysis, budget control, product analysis and sales combining, economic reporting and costs and results statistics, new production technologies control, management accounting information systems design, decision making cost determining assistance, new technologies investment definition, etc.

Expert system applications in the cost accounting and management accounting

There are very few expert system applications in the cost accounting and management accounting. These are mainly theoretical in nature (Akers et al., 1986; Bouche and Retour, 1986; Estrin, 1988; Shim and Rice, 1988; Böer, 1989a, 1989b; 1989c). Generally the applications developed in this domain are composed by two modules: a module which computes by means of traditional information technology or with a decision making aid tool (e.g., an electronic spreadsheet, a statistical package, ...), and an expert system module which carries out interpretation, comparison, diagnosis, and forecasting decision processes. A very important feature of these applications is that they are specific for each firm and problem type in the organization. Another important feature of these systems is their capability to read data files and to link with the other databases in the firm, so it is possible to have available fast information to make decisions. The following is a list of well-known expert systems:

1) SYSTEM NAME 2) REFERENCES 3) ORG., INSTITUTION	4) APPLICATION DOMAIN AND SYSTEM FEATURES BRIEF DESCRIPTION 5) DEVELOPING TOOL
1) BUCKS (Business Control Knowledge System) 2) Brown and Phillips, 1990. 3) Digital Equipment Corp. (DEC).	4) Assists in the analysis of division project performance and the advisory tasks in each region. The system considers the resource and environmental differences among the different regions in a country, as well as the long-term effects of changes in the short-term intervention. It values net operating income and business contribution compared with the budget and net operational income. The system is integrated in other DEC expert systems.
1) ICOR Material Subsystem (Integrated Capital and Operations Reporting) 2) Brown and Phillips 1990. 3)EXXON. Purchased from Atlantic Richfield Co., and adapted and improved by Andersen Consulting.	4) ICOR is a computer-based system that integrates 11 subsystems. One of these modules, the Material Subsystem, is an expert system that assists in the pricing of material transfer at EXXON. The system has three knowledge bases, which are used to transfer pricing suitable for an inventory or transferred equipment with or without transfer of ownership.
1) ICS (Integrated Consulting System) 2) Syed and Tse 1988. 3) SRI International.	4) Strategic planning and management in industries of highly different products and production facilities. The main goal is to analyze and forecast competition in industries, integrating the most significant aspects in the business, marketing, technologies and costs. The ICS integrates four expert systems. A assesses market needs and its power. B assesses business goal and market portfolio evaluation. C rationalizes the solution and D identifies adopted strategies.

	5) The database and logical procedures have been developed in QUINTUS PROLOG, and the analytical procedures are in C.
1) INVENTORY EXPERT SYSTEM 2) Ghiaseddin et al. 1990.	4) It assists inventory control managers to organize information about product demand and supplier stock, in order to select the best inventory management policy, given the goals and objectives fixed by the firm. The system performance is contained in two knowledge bases and an historic database: (1) the inventory model knowledge base, which contains the knowledge related to demand parameters, provision and costs; (2) the solution knowledge base, which contains the knowledge required to select a solution procedure and put it into practice, and (3) the historic database, containing product demand, provisioning and cost data. 5) GURU expert system shell. Also has a simulation procedure written in FORTRAN language.
1) SECOCET (Decision supporting expert system applied to a processing firm cost control) 2) Moreno et al. 1991; Gallizo and Moreno 1992. 3) Universidad de Zaragoza.	4) A decision support expert system to assist in cost and variance analysis in a specific department of a firm manufacturing bricks and tiles. The specific department chosen to prototyping was the loading-drying shed unloading as a previous step for a further study in the whole production process. The system has four modules. The first three modules constitute the decision support system (DSS) and the fourth is the expert system itself (ES). The first module explains the firm's production process and costs per each department. The second module inputs the budgets and actuals of every component operating on the production process. The third module assesses the cost and variances between budgeted and real data. The fourth module is an ES containing an expert's knowledge in cost control and aims to analyze and correct the most important variances between budgeted costs and real cost. 5) The first three modules, the DSS, are developed in C, and the fourth, the ES, in Prolog.
1) XPR 2) Michel 1988. 3) Institut Superieur des Affaires (ISA) en Jouy-en-Josas.	4) It diagnoses management control systems. The system executes an economic and financial diagnose, as well as a technical analysis of the management control elements. The system was also used as a training method using a case study in order to diagnose several systems in other firms. 5) Prolog Language.
1) XVENTURE (X for expert system and VENTURE for risky business) 2) Sullivan and Reeve 1988; Koval 1989.	4) It is a multipurpose expert system supporting the decision on new investments in new production technologies. The system decision process is based on an heuristic analysis about six wide justification subjects: (1) actual management options to invest for a future development, (2) to adjust the firm strategic business plan with its technological plan, (3) to modify the accounting tasks in order to show the changes made in the cost models due to the increase proposed in the capital intensity, (4) to balance the uncertainty in the business environment and its own technology, (5) to consider the benefits to obtain improving the manufacturing flexibility, quality and productivity, and (6) to value the traditional checks about the features of proposed projects for these to be rejected. 5) EXPERT 4 Package.

Expert Systems In Financial Accounting

General Domain Features

Financial accounting "aims to prepare the financial statements which report on the business income and wealth, and for that it submits to treatment and analysis any transactions produced between the aforementioned economic unit and the world outside" (Cañibano, 1982, p. 28). Its main goal is to prepare financial statements to provide the information needed by different users in the firm about the organizational results and wealth. A very important feature of financial accounting is its close relationship with accounting and trading regulations, because it is ruled by a series of generally accepted accounting standards and principles, issued by the Government and reputable boards in charge of issuing

accounting standards (e.g., SEC, FASB, AECA), which grant homogeneity and reliability of financial information against third party.

Expert system applications in the financial accounting domain.

Financial accounting is the accounting sub-domain in which less expert systems have been developed. The applications developed have focused mainly on the following subjects: legal regulations and accounting principles, accounting regulation understanding, non-tax legal advisory, financial statement consolidation, financial statement analytical review, foreign currency transactions, accounting information systems design, accounting entries, etc. In the following diagrams some examples of these systems are shown:

1) SYSTEM NAME 2) REFERENCES 3) ORGANIZATION, INTITUTION	4) APPLICATION DOMAIN AND SYSTEM FEATURES BRIEF DESCRIPTION 5) DEVELOPING TOOL
1) **AGGREGATE** 2) O'Leary 1987a	4) It assists the accountants in designing accounting information systems and financial statements. 5) PROLOG Language.
1) **COMPTA** 2) Gervais and Stepniewski 1986; Stepniewski 1987.	4) Theoretic development of an ES to carry out the accounting entries of a sale invoice. 5) SNARK Language.
1) **CONSOLIDEX** 2) Bonson and Orta, 1991.	4) It is a prototype expert system aimed to understand the standards about consolidated annual accounts of a corporate group, contained in 42nd and following articles of the Spanish Commerce Code. 5) CRYSTAL Shell.
1) **CONTA** 2) Casamitjana 1991	4) It is a prototype expert system to carry out the sale invoice accounting entries. 5) GURU Shell.
1) **ELOISE (English Language Oriented Indexing Systems for EDGAR)**. 2) O'Leary 1987b; van Dijk and Williams 1990. 3) Arthur Anderson & Co., commissioned by the SEC (Securities and Exchange Commission).	4) Is an indexing system to detect concepts and predefined ideas in the proxy statements, linked to EDGAR database (Electronic Data Gathering, Analysis and Retrieval).[1] It has an knowledge base containing English grammar knowledge, sentence structure and meaning of words and idioms, and a SEC knowledge base containing specific knowledge about items for the SEC as well as vocabulary specific to proxy statements. 5) LISP Language.
1) **FSA (Financial Statement Analyzer)** 2) Mui and McCarthy 1987; O'Leary 1987b; Murray & Murray 1988; van Dijk & Williams 1990; Keyes, 1991 3) Developed by Arthur Andersen & Co. commissioned by the SEC during EDGAR project pilot stage (Electronic Data Gathering, Analysis and Retrieval) (see ELOISE)	4) It analytically reviews every entry in business financial statement. The FSA checks all kind of documents presented by the company, whether in paper or electronically. The system enables to identify frauds in any kind of format, pagefoot or wherever comments. It executes ratio analysis using as an information source business annual reports (10K). It understands the balance sheet, profit and loss statement and pagefoots. The FSA contains the accounting knowledge needed to understand the financial statement, and the financial knowledge to execute any ratio analysis. The system has two knowledge bases. A first knowledge base contains accounting and financial knowledge, and the second contains the semantic structures managing the pagefoot process. 5) KEE Sheet. Working in Symbolics LIPS machines.
1) **GRENSIDESE**	4) Legal advise about non-competitive state agreements with the British

1 EDGAR is a system which enables to recover electronically files containing the financial statements required by the SEC, without having to send the business documents.

2) Gambling 1985; Arnold et al. 1985; Connell 1987	Defense Office. 5) SHELLS
1) **LESSEE** 2) Jih, 1991.	4) It is an expert system prototype for rent accounting, according to financial accounting FASB standards which affect the rent accounting. 5) GURU Shell.
1) **PURPOOL** 2) Smith et al. 1991	4) The system helps to determine if the business combining must be addressed as a purchase or as a consortium. The system evaluates 12 criteria according to opinion no 16 of APB "Business Combining". 5) VP-EXPERT Shell.
1) (Unnamed) 2) Bonson, 1991	4) ES prototype for determining adjusts and removals in the statement of changes in financial position.

Financial Statement Analysis Expert Systems

General Domain Features.

"Financial statement analysis, using certain techniques, tries to investigate and ascertain through the accounting information the causes and effects in managing the company to reach that point, and then to forecast on certain limits... its growing in the future, in order to make consistent decisions". (Urías, 1992, p. 179). The financial statement analysis can be divided in three stages: (1) exam, (2) analysis and understanding, and (3) suggestions. In the first stage, an exam or revision of accounting documents is carried out (i.e., balance, profit and loss statement, report, statement of changes in financial position,...) using a series of techniques or specific procedures, as: wealth block comparisons, percentages, index number, ratios, trends, etc. Then, in the second stage, the information obtained in the first stage is analyzed and understood, and a diagnosis about the actual moment and the management performed is made. Finally, in the third stage, some forecasts are made and some solutions are indicated in order to improve the future state. Moreover, all these studies and analysis are commonly performed from three different points of view: wealth analysis, financial analysis, and economic analysis. (Alvarez, 1990; Rivero Romero, 1990; Rivero Torre, 1991; Urías, 1992).

Expert systems applications in the financial statement analysis domain.

Most expert systems developed for financial statement analysis have two modules. a conventional computer-based module that performs computations alone or assisted by a spreadsheet, and an expert system module that performs the data analysis, understanding, and reporting processes (usually through a word processing software). In the following figure some of these systems are shown.

1) SYSTEM NAME 2) REFERENCES 3) ORGANIZATION, INSTITUTION	4) APPLICATION DOMAIN AND SYSTEM FEATURES BRIEF DESCRIPTION 5) DEVELOPING TOOL
1) AFIN (Analysis Financiero de Balances) 2) Instituto de Ingeniería del Conocimiento 1992; Rodríguez 1991; Fortuna Lindo et al. 1991.; Zaccagnini et al. 1992. 3) Instituto Universitario de Ingeniería del Conocimiento de Madrid.	4) It performs a business financial statement analysis according to the Spanish Accounting General Plan issued in 1990. It studies two years consecutive the balances and income statement, report, statement of changes in financial position, it performs tables and treasury ratios, the leverage coefficient, the economic and financial profitability, etc. Then it presents a report diagnosing the business state with some suggestions to improve it. 5) In personal computer: The Integrated Reasoning Shell (TIRS) Runtime. In mainframe: Expert System Environment (ESE).
1) AIDE (Assistance Informátisée au Diagnostic	4) It assists in the diagnose of business in the «Centrale de bilans de la Banque de France». The rule base consists in two blocks: a financial block,

d'Entreprise) 2) Degos 1991. 3) Centrale de bilans de la Banque de France.	calculated on the «Centrale de bilans» business analysis structure, and another economical block focused on competition, development and strategy. The system provides a report studying the business position, its potentiality, results and strategy. 5) 1st LISP Language, 2nd APL Language.
1) ALFEX 2) Connel 1987; Prado 1991. 3) Alvey Financial Community Club; Helix Software Consultants and Expert Systems International.	4) ALFEX is an expert system development project funded by the Alvey Financial Community Club. This project has as a goal to develop expert systems able to advise on the financial health of a business, as well as develop knowledge bases and tools suitable to develop these systems. It provides a report on the business financial health with charts, sales forecasting, ratios, sensitivity analysis etc. 5) PROLOG Language.
1) ANALYSIS 2) D'hoeraene 1990. 3) CERG Finance.	4) Classifies functionally the balance sheet and income statements, assesses the economic and financial flows, profitability, development potentiality, asset management, financial soundness, statement of changes in financial position. It provides charts and a report on the profitability and financial policy.
1) ANIBAL 2) ERITEL 1991; Nuñez 1991; Fortuna et al. 1991. 3) ERITEL.	4) Assists financial analysts in valuing trading and financial management of a company. It executes financial and economic analysis of the business, from a static as well as a dynamic point of view. It has two modules: the first assesses the ratios, charts and so on, while the second asserts conclusions and provides an analysis report, with emphasis on the strengths and weaknesses. 5) ART-IM Shell.
1) FINEX 2) Kerschberg and Dickinson 1988a, 1988b; Prado 1991.	4) Assists in the financial statement analysis of an oil wholesale business. The system assesses the financial ratios from the data provided by the profit and loss statement and balance sheet. 5) The system has three modules: (1) A Lotus 1-2-3 electronic spreadsheet, (2) BASIC package, and (3) a program written in micro-PROLOG.
1) FINEXPERT / FINEXPRO FINESPRO is an improved version of FINEXPERT (Degos, 1991). 2) Schaefer 1987; D'hoeraene 1990; Degos 1991;Prado 1991. 3) Experteam.	4) It helps analyzing financial statements and providing financial reports. Developed by the Department of Finance of the Centre d'Enseignement Supérieur des Affaires (CESA). The system analyzes the financial statement in three groups: business profitability, financial strategy, and inherent risk. Then it provides a report on the business financial management thus indicating the strengths and weaknesses as well as some suggestions for its improvement. 5) PERSONAL CONSULTAN PLUS, linked to MULTIPAN spreadsheet (the advanced version FINEXPRO can use MULTIPLAN, LOTUS 1-2-3 or SYMPHONIE packages).
1) FSA (Financial Statement Analyzer). 2) Mui and McCarthy 1987. 3) Arthur Andersen & Co., commissioned by the SEC (Securities and Exchange Commission) de EE.UU., during the EDGAR project pilot stage (Electronic Data Gathering, Analysis, and Retrieval) (see § also 5.2)	4) Analytical review of a financial statement in the understanding stage of financial statement analysis. The system analyzes the ratios using the reports that American companies must submit to the SEC. The system incorporates natural language techniques in order to analyze the balance texts, statements of income, and page-footings enclosed. It is designed to link with the EDGAR database. 5) LISP Language.
1) PRÉFACE-EXPERT (Progiciel d'Expertise Financière en d'Analyse pour la	4) A forecasting expert system. The Préface-Expert works linked to Préface-Tableur module. The Préface-Expert, from the data provided by the spreadsheet and the Préface-Tableur (i.e., tables, ratios, profitability threshold,

Création d'Enterprises). 2) Senicourt 1987; D'Hoeraene 1990. 3) Ordimega.	working capital, cost structure, ...) analyzes the structure and profitability in the improving firm, the treasury trends, capital profitability, financing structure, forecasting accounts, etc. Subsequently two other modules were added: The Préface-Eao and the Préface-Synthèse. The Préface-Eao presents specific commented definitions and charts. The Préface-Synthèse provides a detailed report containing data, comments and suggestions by the expert system in 3 sections: exploitation, balance and treasury. 5) The Préface-Expert is developed under the GURU shell, linked to Lotus 1-2-3.
1) SAGE 2) Sanz Portell 1991. 3) Banco Bilbao Vizcaya and Sema Group System.	4) Business financial and management analysis. The system analyzes the financial statement and the business qualitative data on the financial and management quality in that company. 5) ADS Shell (Aion Development System).
1) SYMEDE 2) Fredouet 1988, Degos 1991.	4) It is a multidisciplinary business diagnosis system consisting of 3 modules: legal, economic and financial modules. The legal module analyzes the business wealth, contractual and social policies; the economic diagnosis module addresses the strategic aspects of the business situation, and the financial diagnosis module analyzes the sales and production activities, and the profitability and financial structure in long and short term. 5) GURU Shell.
1) VENTUREEXPERT 2) D'Hoeraene 1990. 3) Experteam. Commercialized in Spain by Regisdata SA	4) The system carries out a business financial diagnosis. It performs profitability analysis, financial strategy and risk analysis. It issues a report on the management and plans to undertake.

Expert Systems In Financial Planning and In Financial Analysis

General Domain Features.

The financial environment has suffered dramatic changes in the last years (e.g., inflation, worldwide economy integration, economy and financial market liberalization, great variety of financial products, increasing tax pressure and continuous changes in laws, ...). Due to this complexity, companies and individuals increasingly demand financial advisory services enabling them to carry out a proper investment policy and financial planning.

The field, known in the Anglo-Saxon area as Financial Management, is commonly known in Spain as Dirección (Administración o Gestión) Financiera. Also in this field there are two significant branches related to specific subjects, for example: Investment Appraisal or Capital Budgeting is its modern denomination, and commonly addresses every problem related to business investments. The area of Financial Analysis, which tries to analyze the financing related problems produced as a result of these investments, and the Financial Planning area studies the short, medium and long term planning in financing investments (Suárez, 1991). In this paper we focus only on the financial planning area, because most expert systems focus specially on solving the problems in this field, although we also mention some systems related to financial analysis and investment appraisal, a field closely related to financial planning.

Business financial planning is the part of business planning that addresses business financial aspects not to forget its non-financial aspects (Suárez, 1991, p. 608). Again, financial planning can be also addressed personally, so giving rise to personal financial planning, which includes, among others, these subjects: investment planning, tax planning, wealth management, insurance planning, retirement planning, treasury management, debt management, etc.

Financial planning, financial analysis and investment appraisal require many procedures among which; net cash flow analysis, internal rate of return calculations, payback period calculations, present value deflation, etc. It also can benefit from Bayesian analysis, simulation models, linear and dynamic scheduling, sensitivity analysis, asset appraisal, capital costing, financial and economic risk, statement analysis and ratio assessment, budgets, etc. (Suárez, 1991; Fernández, 1991).

Expert system applications in the financial planning and in the financial analysis domain.

In order to perform the above functions expert systems may be added to the traditional toolset. It is very difficult to quantify parameters in mathematical models because it is mainly based on heuristic knowledge, available only from the expert, acquired by this person personally after many years of experience in trying to solve a problem on a continued basis. The expert system technology is very useful in this type of tasks because it enables using heuristic knowledge and the invaluable assistance of financial planners and analysts.

Most expert systems applications developed in the financial planning and financial analysis commonly include two modules:

(1) a module that executes the assessments by means of the traditional computer science or any other type of decision aid tool (e.g., spreadsheets, simulation systems, optimizing models, etc.), and
(2) the same expert system module, that carries out the data analysis and understanding processes as well as the reporting process (usually with a word processing package).

Financial planning and financial analysis expert systems have improved substantially, thus challenging the opinion that expert systems are applied in very narrow domains. This is sue mainly to the fact that information is qualitative and very formalized in nature, and a quite improved theoretical frame exists which allows to deal systematically with a very wide group of variables (Connell, 1987, p. 225). Now we present a list of well-known expert systems.

1) SYSTEM NAME 2) REFERENCES 3) ORG., INSTITUTION	4) APPLICATION DOMAIN AND SYSTEM FEATURES BRIEF DESCRIPTION 5) DEVELOPING TOOL
1) AAFINPLAN (A modified version of PLANMAN system) 2) Phillips et al. 1991. 3) Arthur Andersen & Co.	4) It provides those firms patronizing Arthur Andersen with financial advice for its employees. The system, according to the information related to each employee (i.e., income, marital status, children, taxes, retirement plans, ...) issues a report containing financial planning suggestions for each individual.
1) Capital Investment System 2) Brown and Phillips 1990. 3) Texas Instruments.	4) It assists the Texas Instruments department managers to make equipment purchasing investment decisions. Describes legal requirements, including the environmental impact regulations. It assesses cash flows and return on investments.
1) CASHVALUE 2) Ash 1985; Connell 1987. 3) Developed by Heuros Development Ltd. and distributed by Hoskyns.	4) Suitable to evaluate investment projects. The system potential uses include: project investments, enhancing the existing operations, cost reduction schedules, purchasing, new risked business and business assessments. It utilizes a cash flow methodology, discounted to assess investments. At the end of the consultation the system provides an evaluation report on the investment project thus indicating: the net cash flows after taxes, funds, tax assessments, working capital adjusts, effects on the year-end closing, risk evaluation, etc. The information can be also presented in graphic form and in spreadsheets to produce a sensitivity analysis. 5) BASIC Language.
1) Client Profiling System 2) Brown 1988; Phillips et al. 1991. 3) APEX (Applied Expert Systems).	4) It assists the financial planners to carry the personal financial planning for individuals with average revenues, between 25.000 $ and 80.000 $. The system uses a customer questionnaire that can be prepared assisted by the financial business or by the employee itself. The questionnaire includes financial data and focus on the client's goals.
1) FAME 2) Brown 1988; Brown and Phillips 1990. 3) IBM.	4) Financial planning for acquiring mainframes. The system addresses the operating cost, annual allowance, software cost and maintenance agreements cost. The system also helps to determine the proper accounting treatment. It provides sensitivity analysis.
1) MANAGEMENT	4) It advises the accountants and financial managers of a big business on

ADVISOR (first called FINANCIAL ADVISOR) (Mockler, 1989; Brown, 1988). 2)Bailey 1985; Michaelsen $ Michie 1986; Connell 1987; Brown 1988. 3) Sloan School of Mngt.	the capital budgeting planning and the capital allowances. Also gives advice on merging, purchasing, qualification decisions, cost controlling, etc. It is based on discounted cash flow method. 5) LISP Language.
1) Objective Financial Systems 2) Brown 1988; Phillips et al. 1991. 3) Objective Financial Systems, Inc.	4) It helps in personal financial planning for people receiving average revenues, income lesser than 30.000$. The system produces or a global financial plan or separated modules, which address retirement planning, education retaining fee, debt management, insurance and risk management, life insurance planning, state planning, housing management, budgets and investments, etc.
1) Personal Financial Analysis 2) Phillips et al. 1991. 3) Price Waterhouse.	4) It provides Price Waterhouse clients employee financial guidance. The system, based one family and economic status information (i.e., revenues, taxes investments, marital status, specific financial goals as retirement financing or children education, ...), prepares a long report providing suggestions for asset management, investment strategies, tax saving strategies, education saving planning, life insurance needs, retirement funds, etc.
1) PFPS (Personal Financial Planning System) 2) Phillips et al. 1991. 3) Chase Lincoln First Bank and Arthur D. Little, Inc.	4) The PFPS is a personal financial planning integrated system including investment planning, debt planning, retirement planning, educational planning, life insurance, budgetary suggestions, income tax planning, etc. The system provides detailed reports for employees of all income ranges.
1) PLANMAN 2) McKell and Jenkins 1988; Brown 1988; Phillips et al. 1991. 3) Sterling Wentworth Corporation.	4) It assists professional financial planners in personal financial planning. The system produces global or modular plans. The system can address analysis of the following modules: (1) tax income and cash flow planning, (2) debts and portfolio management, (3) wealth growing management (e.g., retirement plans, education planning, ...), (4) property planning, (5) risk management (e.g., insurance and disability analysis and planning. The system allows "what-if" analysis and provides a large range of reports and charts. 5) C Language.
1) PLANPOWER 2) Stansfield and Greenfeld 1987; Connell, 1987; Brow 1988. 3) Applied Expert Systems, Inc. (APEX)	4) Assists bank and accounting financial planners in global financial planning, for individual customers and companies. Gives advice on several areas: tax , including investment management, retirement plans, risk management, treasury and loan management, etc. The system provides detailed financial plans. Financial plan documentation includes: (1) a diagnosis about the client status, suggest actions to be taken, (3) explanation and reasoning of these actions, (4) information on the relevant ground about financial matters. It allows sensitivity analysis to be made. 5) LISP Language.

Conclusions

Expert systems are becoming a reality in the accounting field, particularly in tasks where professional judgment is required. Their usage in accounting will have significant advantages. Among the main benefits we find: (1) maintenance of expert knowledge in the firm, (2) sharing of expert knowledge through the firm, (3) enhanced capacity of experts to manage large volumes of data and carry complex analysis, (4) improved quality and more efficient professional work, (5) flexible decision making advice, (6) deeper understanding of the expert knowledge, (7) enhanced staff productivity, (8) increased services offered by the business, and (9) utility as an education and staff training tool.

Using expert systems will also produce significant changes in business and organizations. For example we can mention the following: (1) changes in the way to structure and organize clerk and accounting procedures in non-structured tasks, (2) staff changing among different departments and functions in the enterprise, (3) changes in the habits that managers and professionals used to have, etc. We must say as well that the use of expert systems will produce important implications on legal and ethics responsibility, because many decisions to be taken, as a result of the answers given by the expert system, can damage to third party and may have important social or ethical consequences.

Expert system applications in accounting enable to cover a very important vacuum in the development of this field. The appearing of these systems has closed a stage in the theoretical and practical development of accounting in which structured tasks computing prevailed, with ordinary computer-based software, but it was not enough in current environments, where furthermore the computing of non-structured tasks is needed. That is to say, with the using of expert systems in accounting it is possible to pass from the simple information management to knowledge management, which is an essential element in the accountant decision-making processes. Also, it is worthy to stress that expert system development has modified dramatically the research methodology in accounting, because it is no more an individual research, but a collective and multidisciplinary research, because developing these systems requires a close contribution of scientists in different fields, and furthermore, big material investments are needed. Therefore expert systems, apart from providing important advantages for the accounting profession, also promise interesting change insights in its conceptual frame and in professional applications.

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on the Return by Identifying the Data Source			

Financial Accounting

The population of financial accounting expert systems is sparser in the period of study. It strikes the researchers that this filed in under-explored and great potential of research exists and has not been fully harvested. Most FASB statements can be positioned as a form of influence diagram, industry effects can be posted as branches or exceptions, other statement idiosyncrasies can be stated in the body of the net, and disclosure decisions can be the conditional variables for guiding financial managers and statement preparers. Early research in accounting has represented financial statements as sets of interconnected equations. Expert systems technology can greatly enrich this axiom and provide the basis for many different types of metaphors.
Table 3 shows that in financial accounting, expert systems are available for cash flow evaluation, analysis of mergers, acquisitions and other investment decisions. Determination of financial status by ratios, leases, and analysis of financial reports filed with the SEC are other areas in financial accounting where expert systems exist.

Table 3: Financial Accounting

Expert Domain	**Reference**	**System Used**	**Tool**
Cash Flow, Project Valuation and Risk Evaluation	Ash(1985)	CASHVALUE	BASIC
	Wilson and Edge (1988)		
	Edwards and Connell(1990)		
Analysis of Mergers, Acquisitions, and Other Business Opportunities	Bernstein(1985)	FINANCIAL ADVISOR	LISP
	Wilson and Edge (1988)		
	Edwards and Connell(1990)		
Determination of Financial Status by Ratios	Wilson and Edge (1988)	FINEX	
Accounting Treatment for Leases by Lessee	Boer and Livnat(1990)	name unknown	VP-EXPERT
	Smith, McDuffie, and Flory(1991)		
Accounting Treatment for Business, Combination	McDuffie(1990)	PURPOOL	VP-EXPERT
	Smith, McDuffie and Flory(1991)		
Analysis of Reports, such as Proxy Statements, Filed with SEC	Sweeney(1989)	ELOISE	
Automatic Selection and Analysis of Corporate Mergers and Acquisitions from an On-line Financial Service	Sweeney(1989)	SCISOR	
An Object-Oriented Programming Approach To Credit Decision Making	Nils Kandelin and Tom Lins(1991)		
Expertise in Assessing Solvency Problems	Jesse F. Dillard and Jane F. Mutchler(1987)		
Knowledge Elicitation and Representation: An Example	Marinus A. Bouwman(1992)		

From Financial Analysis			
Some Thoughts on the Engineering of Financial Accounting Standards	Jagdish Gangolly		

Personal Financial Planning

Personal financial Planning systems have evolved to a very sophisticated set of procedures. It allowed for the development of many packages sold independently or as part of a financial advisor's services. While stated separately, as it deserves a section of its own, these packages, mainly of commercial (not research) nature are heavily interconnected with the other types. Actually, they could be considered as part of the first circle in figure 2. Carol Brown's research extensively compares and evaluates these packages.

Due to the constant change in tax laws and regulations, financial planners have developed various types of expert systems to aid in financial planning for individuals. Most of the systems are based on the range of income of each individual. Some expert systems even give advice on taxation, investment, and estate and retirement planning.

Table 4: Personal Financial Planning

Expert Domain	Reference	System Used	Tool
Providing Financial Planning for Those with Income Over $60,000	Kempin(1983)	AYCO	
	Phillips, Brown, and Nielson(1990)		
	Phillips, Brown, and Nielson(1991)		
Advice in Taxation, Investment, Estate, and Retirement Planning	Apex(1986)	PLANPOWER	LISP
	Edwards and Connell(1990)		
	Phillips, Brown, and Nielson(1990)		
	Phillips, Brown, and Nielson(1991)		
Providing Financial Planning for Those with Income Between $25,000 and $200,000	Mowatt(1987)	CLIENT PROFILING SYSTEM	
	Phillips, Brown, and Nielson(1990		
	Phillips, Brown, and Nielson(1991)		
Providing Financial Planning for Those with Income over $50,000	Niswander(1987)	OBJECTIVE FINANCIAL SYSTEM	
	Phillips, Brown, and Nielson(1990)		
	Phillips, Brown, and Nielson(1991)		
Providing Financial Planning for All Taxpayers	Barbee(1987)	PERSONAL FINANCIAL ANALYSIS	
	Phillips, Brown, and Nielson(1990)		
	Phillips, Brown, and		

	Nielson(1991)		
Providing Financial Planning for Those with Income Between $25,000 and $500,000	Cann(1987)	PERSONAL FINANCIAL PLANNING SYSTEM	
	Phillips, Brown, and Nielson(1990) (PFPS)		
	Phillips, Brown, and Nielson(1991)		
Providing Financial Planning for All Taxpayers	Whittenburg (1987)	PLANMAN	
	Head(1989)	AAFINPLAN	
	Phillips, Brown, and Nielson(1990		
	Phillips, Brown, and Nielson(1991)		
	McDuffie, Flory, Humphreys (1993)		

Management Accounting

At this time, expert systems are also widely used in the management accounting area. International Business Machines' FAME is an example of such a system. FAME is used to assist customers with mainframe capacity decisions and financial planning for the acquisition of mainframe computers by purchase, conditional purchase or lease. Texas Instruments' capital investment system and Exxon's revenue recognition, transfer pricing, cost flow and accumulation, and evaluation of credit worthiness are other examples of the expert system developed for management accounting purposes. Extensive surveys of applications in management accounting can be found in several pieces of Carol Brown's work and Alan Sangster's work. Sangster display a series of applications of management accounting in the United Kingdom, proving great international penetration of the filed.

Analysis of variances for cost control, budgeting and future planning, and division evaluation are also part of the application of expert systems in management accounting. Expert systems in the management accounting area cover asset allocation and performance attribution, and also design and development of management information systems.

(e) MANAGEMENT ACCOUNTING

Expert Domain	**Reference**	**System Used**	**Tool**
Financial Planning for the Acquisition of Mainframe Computers by Purchase, Conditional Purchase, or Lease	Brown and Phillips(1990)	FAME	
Preparation of the Investment Decision	Brown and Phillips(1990)	Capital Investment System Reports	
Revenue Integrated Recognition Transfer, Pricing, Cost Flow and Accumulation, and Evaluation of Credit Worthiness	Brown and Phillips(1990)	Capital Reporting and Operations (ICOR)	COBOL
Assistance in Buying, Pricing, Promotion Planning, and Retail Space Allocation	Phillips(1990)	Grocers' Buyer's Workbench	
Analysis of Variances for Cost Control, Budgeting and, Future Planning	Brown & Phillips(1990)	NEXPERT	Arthur D Little's Expert System
Division Evaluation Program	Brown and Phillips(1990)	BUCKS	

Design and Development of Management Information Systems	Englard, Kiss, McCombs, and Schwartz(1989)	name unknown	
Asset Allocation and Performance Attribution	Valentine(1988)	name unknown	

Conclusion

During the past fifteen years, expert systems have made a tremendous contribution to the accounting profession. Because of the high cost of developing such systems, only large accounting firms were actively involved in the development of most expert systems for accounting purposes. Expert systems will continue to play an increasingly important role in the work of accountants in the future. They can assist less skilled practitioners in handling routine as well as complex tasks; they can easily handle routine screening and categorizing tasks; and they can be used as decision aids by financial analysts, auditors and individual companies. As with personal computers, today's accountants will need to understand the application of expert systems to be able to perform effectively and efficiently in the workplace.

While much research has been performed in the audit field, its deployment in practice has been limited and is still in pre-paradigmatic stage. The applications is tax are very promising and have been deployed for widespread usage by the IRS and in personal tax packages. The applications in financial accounting are very promising but require much research and study. The same is true for management accounting and costs. Finally, personal financial planning packages are here and widely deployed for profit. These show that proper choice of domain and investments can pay off and benefit large portions of the economy.

Another dimension of the phenomenon however makes us much more optimistic. The expert systems paradigm has deeply influenced information systems design and implementation. Features such as the separation of the knowledge engine from the data engine, the why? Help feature, integrated designs of expert systems shells, have seriously influenced information systems design and are progressively appearing in the ubiquitous personal financial management tools. We expect these effects to route back to research and to guide us to an entire new set of paradigms in systems design and implementation.

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Part II: The Neural Net Paradigm.

A Framework for Evaluation of Neural Network Investment Systems for Prediction of Takeover Targets

John J. Cheh,* Randy Weinberg,** and Ken Yook***

Abstract

The merits of neural network applications to financial studies have been documented in the areas of business failure prediction, debt risk assessment, and stock price predictions. Yet, efficacy of the neural technology as an investment expert system is still yet to be established rigorously. One concern in this research area is the lack of a standard measuring framework for productivity of various neural network-based investment systems. Without such a standard, effectiveness and efficiency of neural network-based investment systems can be difficult to assess. In this paper, we propose such a standard framework.

Introduction

The purpose of this paper is to provide a framework in which neural network[4] researchers and investment professionals can find valuable measurement standards for evaluating the efficacy of neural network investment systems (NNIS). Investment professionals increasingly rely on neural network technology for confirming their decisions, or use the neural network technology as a feedback mechanism to improve their investment productivity. Providing a standard measuring framework may aid investment professionals to evaluate the usefulness of various NNIS.

To facilitate such a standard, we use an example NNIS that identifies firms that are likely takeover targets. By focusing on a particular subset of stocks, an NNIS can take advantage of unique attributes that the stocks under study might possess. Such selectivity can improve the performance of the NNIS.

Although various authors explore the usefulness of neural networks as financial and investment tools in the areas of business failure prediction, debt risk assessment, and stock price prediction (Tripp and Turban [1993]), there has been little work done on the utilization of the neural network technology for prediction of stocks that will be acquired. By focusing on this less-developed area, we may get more insights into the issues related to the performance of an NNIS.

All previous studies for prediction of takeover targets utilized conventional methodologies such as discriminant analysis, logit analysis and probit analysis (Stevens [1973], Harris, Stewart, Guilkey, and Carleton [1982], Hasbrouck [1985], Palepu [1986]). They mainly focused on finding the motives of takeover activities and constructing theories of takeovers rather than the prediction technology itself. For instance, most studies attempted to find financial variables that are important in identifying takeover targets rather than developing and evaluating investment systems for predicting such target firms. We examine issues related to evaluation of NNIS by utilizing their findings.

[4] Throughout this paper, *neural network is* meant to be *artificial neural network* unless we indicate otherwise.

In Section 2, we briefly review neural network technology, and its investment applications. In Section 3, we provide a framework in which a methodology is considered for the performance measurement of NNIS. We conclude the paper in Section 4.

Neural Network Technology And Its Investment Applications

An artificial neural network system is a computer model that emulates the structure of the brain. Neurons in an artificial neural network are simple processors connected in complex networks of paths to other neurons or external sensors. Neurons receive input signals, or values, from other neurons, and produce an output signal which is communicated to other neurons.

Each connection between nodes in a neural network is weighted. The strength of a connection between any two neurons in a network is indicated by the value of this weight. Since all the weights in a network can be different, each connection in an artificial neural network thus has its own strength, or relative importance. The "knowledge" or learning of the network is stored as the value of the weights between nodes, and the system learns new information by adjusting the weights.

More precisely, consider a typical node, node i, in a neural network. Consider the other nodes to which node i is connected. Each value sent to node i is modified, or weighted, by the strength of the corresponding connection. Thus, for example, if node j sends output value outputj to node i, the value of the signal reaching node i is equal to wjioutputj, where wji is the weight of the connection between node j and node i. Since node i receives signals from many nodes, its actual input is given by the expression:

$$input_i = \sum_j W_{ji}\, ouput_j$$

Each node transforms its inputs into an output value through the use of a transfer function. A design issue in neural network applications is to select an appropriate transfer function to generate the output values. While numerous transfer functions have been proposed, one of the most popular and successfully used transfer functions is the sigmoid function which produces a continuous value in the range (0,1):

$$output_i = \frac{1}{1 + e^{gain + input_i}}$$

where gain is a parameter determined by the network designer.
Nodes in a neural network are usually grouped in layers. In a simple neural network, processing nodes can be grouped into one input layer, one middle, or hidden layer, and one output layer. A neural network with three input processing nodes, four hidden nodes, and two outputs can be shown as follows.

Figure 1: An Artificial Neural Network with one hidden layer

The ability to "learn" is what distinguishes neural networks from other types of traditionally statistical investment decision support systems or expert systems. Neural networks use training examples to learn, iteratively adapting the interconnection weights in order to produce outputs that are reasonably close to what is expected. When satisfactory performance on the training data is achieved, training ceases. Once trained, neural networks are validated on test data, and then deployed to evaluate future cases. Contemporary neural networks employ a number of different learning rules and training concepts.5

Numerous research projects have taken advantage of the above learning ability to improve various financial and investment productivity. Studies on business failure prediction, debt risk assessment, and security price predictions have provided ample evidence that neural technology can provide alternative investment systems. Cheh, Weinberg and Yook (1995), Yoon and Swales (1991) and Kamijo and Tanigawa (1990) show that neural technology can be a useful tool for investment professionals.

Yoon and Swales (1991), in a stock price prediction study, demonstrated that neural network technology could significantly improve the predictability of stock price performance when compared with multiple discriminant analysis. Nevertheless, investment professionals may be not only interested in knowing the ability or reliability of neural technology as an investment tool, but also ability to outperform the market or other trading techniques.

In the following section, we will provide a framework to measure the productivity of NNIS.

[5] For a further discussion, see Zurada (1992).

A Framework For Efficacy Evaluation Of Nnis

There are a number of ways of proposing a framework in which comparisons of NNIS can be made. In this study, we propose a framework by discussing NNIS performance evaluation activities using takeover targets as an example. The framework consists of data collection, filtering system, NNIS design and development, and NNIS investment productivity performance.

Data Collection

Data for our example study are collected from COMPUSTAT and CRSP databases. Earlier work in financial markets allow a relatively manageable number of variables to be selected for the NNIS evaluation. The previous studies (Stevens [1973], Harris, Stewart, Guilkey, and Carleton [1982], Hasbrouck [1985], Palepu [1986]) suggested that these selected variables play an important role in predicting the takeover target firms. The variables are: (1) size, (2) market-to-book ratio, (3) price-earnings ratio, (4) leverage, (5) liquidity, (6) growth, (7) dividend payout ratio, and (8) return on equity.

Using these variables, Cheh, Weinberg and Yook (1995) demonstrated that a neural network system can classify takeover target firms out of the testing set with accuracy over 60%. In the study, for the neural network analysis, a data set of 1063 firms, 837 firms were selected at random to be used for training, and the remaining 226 used for testing.
Each variable is defined in the table following:

TABLE 1: VARIABLE DEFINITION

Variable	Definition *
Size	Log of total net book value [#6]
Market-to-book ratio	Market value of common equity ÷ book value of common equity [(#25 x #24) ÷ #60]
Price-earnings ratio	Market value of common equity ÷ Total earnings [#24 ÷ #58]
Leverage	Long term debt ÷ Common equity [#9 ÷ (#10 + #11)]
Liquidity	Cash and equivalent ÷ Total assets [(#1 + #2) ÷ #6]
Growth	Current year's sales ÷ Previous year's sales -1 [(#12 ÷ previous year's #12) - 1]
Dividend payout ratio	Dividend per share ÷ Earnings per share [#26 ÷ #58]
Return on equity	Net income ÷ common and preferred equity [#18 ÷ (#10 + #11)]
* Note: COMPUSTAT item numbers are shown in brackets for each variable.	

Data set may include the three years of history for the training set. That three years of history includes the year of acquisition and the two prior years. The financial characteristics that make a firm attractive as an acquisition target may appear much before the actual acquisition occurs.

To evaluate the investment performance of NNIS, the data on stock prices and returns of sample firms are collected. The stock prices to be used are the closing stock prices of the sample firms on the last day of each month. Firms with missing information are eliminated from both training and testing sets.

To compute the return on the market portfolio, the market return is operationalized as the realized, market-value-weighted, and monthly return for firms on stock exchanges. This information can be obtained from CRSP database.

For a given number of firms under study, the firms in the data set are grouped into four categories as shown in a table below.

Classification	Acquired Group	Non-acquired Group
Training (or Learning) Set	(1)	(2)
Testing Set	(3)	(4)

An NNIS is trained using firms in (1) and (2), recognizing value patterns of variables in two different groups. Once an NNIS is trained, it is tested with firms in a new set, which includes firms in groups (3) and (4).

Filtering System

In evaluating an NNIS, a framework should articulate a means of filtering data so that contamination of the results can be reasonably managed. Contamination of results can arise from various of sources, including inherent underlying patterns of stock attributes.

To reduce such bias, the framework should provide a built-in filtering system to prevent the bias of the results from such contamination. A number of mechanisms can be built into a filtering system in a measuring framework to reduce the bias from such contamination. For example, Oppenheimer (1984,1986) found abnormal risk-adjusted returns in stock investment, using Graham's valuation models (1973). However, the results of Oppenheimer's abnormal return studies (1984, 1986) could be driven by Basu (1977)'s high earnings yield effect: portfolios of low price/earnings (P/E) ratio stocks earned abnormal risk-adjusted returns. Without controlling P/E effect, therefore, investment professionals may not be able to differentiate between the relationships of the P/E ratios and of NNIS processing elements, regarding portfolio performance.

To mitigate this P/E effect, for example, the distribution of P/E ratios across portfolios under study can be randomized. Following the portfolio randomization by Basu (1983), and Bildersee, Cheh and Zutshi (1993), firms in training set and testing set should be selected as members of five randomized P/E ratio sets. The firms are sorted ascending order, by their P/E ratios, and divided into five approximately randomized equal quintiles

$$Q_i \ (i = 1, ...5)$$

The purpose of this procedure is to distribute any P/E ratio patterns randomly across each P/E quintile. This eliminates any P/E ratio- induced systematic patterns across those quintiles.

Basu (1983) found that the P/E effect was dominating the firm size effect in his abnormal return study, and observed that the size effect vanished with control of P/E ratio. The size effect arises when small size firms outperform large size firms on a risk-adjusted basis. Since a neural network algorithm may be biased by such patterns, this effect needs consideration when a filtering system is designed for NNIS development.

Another source of bias can be caused by bull and bear market fluctuations. To reduce this bias, firms can be grouped into bull period sets and bear period sets. By training and testing an NNIS in each set, the bias on the results from such market fluctuations can be reduced.

NNIS Design and Development

For evaluating various NNIS, a number of different network designs can be considered. In each NNIS, different combinations of the number of nodes for an input layer, a hidden layer, and an output layer can be employed in the design. In addition to a typical backpropagation algorithm,[6] other algorithms and convergence criteria can be used during the training of the neural network.

Different combinations of NNIS design parameters such as the number of processing nodes can be important for NNIS performance. For instance, as noticed in the studies by Cheh, Weinberg, and Yook (1995), and Yoon and Swales (1991), the number of hidden nodes can affect the prediction rate of a neural network.

Productivity Measurement of NNIS

For measuring productivity of various NNIS, rates of return from the investment placed in a set of predicted target firms can be compared with rates of returns of selected market indices. The rate of return from each quintile testing set portfolio is compared with that of a model market portfolio.

For the productivity evaluation of NNIS, following Bildersee, Cheh and Zutshi (1993), such comparisons can be done in two stages, first using aggregate portfolios and then controlling for P/E ratios, and size.

For the aggregate analysis stage, all firms are pooled into bull and bear period sets. In each bull or bear set, the return portfolio of an NNIS predicted acquired firms is compared with the performance of the market index.

Following, Bildersee, Cheh and Zutshi (1993), the aggregate analysis can also be repeated using assumptions about accounting data availability. The first alternative is based on the assumption that accounting data are available of preliminary earnings numbers and the publications of quarterly data for the first three quarters of the fiscal year. The second alternative is based on the assumption that the accounting data are available three months after the end of the fiscal year.

For the randomization analysis stage, the analysis is run after controlling for P/E ratios. The analysis is separately carried out with randomized quintile training and testing sets, for a given bull or bear period.

Conclusions

In this paper, we provided a framework for evaluating NNIS of investment in takeover targets, which can be generalized in evaluating NNIS of other stock investment techniques. By employing such NNIS evaluation processes, usefulness of this framework can be supported in future work.

This framework can be extended to include other types of investment strategy in NNIS using different holding periods. As Cheh, Bildersee, and Zutshi (1993) did, a monthly rebalancing strategy can be employed. In that case, the testing set needs to be constantly rebalanced every month, as if portfolio trading were done at the beginning of each month. In that case, there will be substantial transaction costs. Also, as indicated by Bildersee, Cheh and Zutshi (1993), the monthly rebalancing and 12 month holding of a portfolio can bring different impacts on the portfolio returns, besides the transaction costs. A number of different holding periods thus can be important consideration for evaluation of NNIS.

[6] This algorithm attempts to minimize the Root Mean Square Error (RMS Error) between the desired outputs of the network and the observed outputs of the network.

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Over and Under Reliance on Internal Controls: Neural Networks versus External Auditors

Susanne O'Callaghan, John Paul Walker and J. Timothy Sale

Key Words: COSO; External Auditors; Internal Controls; Treadway Commission; Neural Networks; Artificial Intelligence

Abstract

This study explores the differences between neural network and auditor assessments of internal control. The research uses the Committee of Sponsoring Organizations Integrated Framework for Internal Controls (COSO) as a basis for studying assessments of internal controls over operations, financial reporting and compliance with rules and regulations (and in particular the resulting under and over reliance on internal controls in these three areas).

Prior experimental results indicate that neural network models can simulate auditors internal control assessments 65% of the time. This research indicates that in making internal control assessments over operations, a neural network model and auditors agree on the appropriate assessment 59.3% of the time; reliance on the network model alone results in over reliance on internal controls 15.5% of the time and under reliance on internal controls 25.2% of the time.

In making internal control assessments over financial reporting, a neural network model and auditors agree on the appropriate assessment 68.9% of the time; reliance on the network model alone results in over reliance on internal controls 11.7% of the time and under reliance on internal controls 19.4% of the time.
In making internal control assessments over compliance with rules and regulations, a neural network model and auditors agree on the appropriate assessment 55.3% of the time; reliance on the network model alone results in over reliance on internal controls 15.6% of the time and under reliance on internal controls 29.1% of the time.

Moreover, no internal control assessment decisions of the network were extremely incorrect. For example, if the auditor expressed a low effectiveness rating over a particular control scenario, the neural network expressed a high assessment rating only once in 309 attempts (less than .324%).

Introduction

Purpose

This study explores the differences between neural network and auditor assessments of internal control. The research uses the Committee of Sponsoring Organizations Integrated Framework for Internal Controls (COSO) as a basis for studying assessments of internal controls over operations, financial reporting and compliance with rules and regulations (and in particular the resulting under and over reliance on internal controls in these three areas).

Research Results

Prior experimental results indicate that neural network models can simulate auditors internal control assessments 65% of the time (O'Callaghan 1994). This research indicates that in making internal control assessments over operations, a neural network model and auditors agree on the appropriate assessment 59.3% of the time; reliance on the network model alone results in over reliance on internal controls 15.5% of the time and under reliance on internal controls 25.2% of the time.

In making internal control assessments over financial reporting, a neural network model and auditors agree on the appropriate assessment 68.9% of the time; reliance on the network model alone results in over reliance on internal controls 11.7% of the time and under reliance on internal controls 19.4% of the time.

In making internal control assessments over compliance with rules and regulations, a neural network model and auditors agree on the appropriate assessment 55.3% of the time; reliance on the network model alone results in over reliance on internal controls 15.6% of the time and under reliance on internal controls 29.1% of the time.

Literature Review

Descriptive Models

Research by Little (1979) contends that a mathematical model should be able to capture decision making. Waller and Jiambalvo (1984) define a descriptive model as one that "...is a representation of how decisions are made in fact, not merely as they might be made in a 'better world.'"[7] Descriptive models are beneficial since they are useful for predicting and explaining empirical phenomena. The prediction capability serves in an anticipatory capacity and can help control further actions.

Waller and Jiambalvo contend that a descriptive model must provide explanations for behavior, thereby providing some causal explanations. They contend that a descriptive model must allow an understanding of the processes embedded in the final decision. The explanatory powers of a descriptive model start with the phenomena and then search out the conditions or laws that might explain the phenomena. In a field experiment subjects can be provided extensive background material that will support their professional judgment. They are allowed an adequate amount of time to respond to the instrument as well as being able to ask questions that clarify. This strengthens external validity. By constructing and utilizing real-world tasks in the experiment and surrounding the experiment with a richer decision context, the generalizability of the research findings increases.

Romano (1986) contends that by interfacing the intuition of people with the data retrieval and computational capabilities of computers, a decision support system can be developed that can adapt to many complex real-world problems. Hammond et al (1986) recognize Brunswick's unique contribution to decision support systems via the Lens Model. Hammond et al's vision for a decision support model is one that concerns itself with realistic research designs that are representative of the environment in which social policy is formulated.

Artificial Intelligence (Neural Networks)

Neural networks offer several advantages over traditional decision support systems. Traditional decision support systems are often grounded in rule based logic. These decision support systems cannot easily be modified for changes in the function being studied or for changes in the environment. Neural networks are grounded in pattern recognition capabilities. Networks can generalize by utilizing known information and drawing conclusions about events that the network has not previously observed (Lawrence 1993). Neural networks require many sample inputs along with known associated classifications. This process allows a network to be trained without specifying if-then rules and without the problem of conflicting expertise in the domain being studied. As a part of the artificial intelligence literature, neural networks have provided accounting information useful for decision making in the areas of "going concern"; commercial bank failures (Bell, Ribar, Verchio, 1990); the analytical review process (Coakley and Brown, 1992); bond ratings (Dutta and Shekhar, 1988); and financial ratios used as analytical procedures (Coakley, 1992).

Internal Controls

Applying neural networks to internal controls makes sense in light of Ashton and Brown's (1980) seminal article in research on internal controls. These researchers contend that:

Expert decision makers often maintain that the simplified representation of their judgment strategies as an additive combination of linear effects is insufficient...[and that] noted researchers in psychology have expressed the opinion that interactive or other nonlinear models will eventually prove superior to linear models for some types of judges and/or tasks.[8]

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[7] William Waller and James Jiambalvo, "The Use of Normative Models in Human Information Processing Research in Accounting," Journal of Accounting Literature 3 (1984), p. 202.

[8] Robert H. Ashton and Paul R. Brown. "Descriptive Modeling of Auditors' Internal Control Judgments: Replication and Extension," Journal of Accounting Research, Vol. 18, No. 1 (Spring 1980), p. 271.

In addition to the suggestion that nonlinear models may enhance judgment decisions, Ashton and Brown suggest that judgmental insight and consensus increase as auditing experience increases, given an internal control evaluation task.

Statement on Auditing Standards No. 55 (SAS No. 55) provides details for the consideration of the internal control structure of a company during an auditing engagement. These guidelines demonstrate the complex nature of the internal control structure and the complexity of the decision-making in internal control assessments. SAS No. 55 also presents the interrelationship of evidential matter by pointing out that interrelationships exist among the control environment, accounting system, and the control procedures.

Felix and Niles emphasize the need for better external validity in auditing research, especially in the context of internal control assessments, to clarify conflicting research results. They suggest that richer experimental settings would enhance this external validity. Enhanced internal control research might include: activities that encompass documentation and learning of controls; planning and evaluation of controls; and re-evaluation of controls throughout the audit.
Within the planning and evaluation of controls' section, they suggest that professional standards on evaluating internal controls do not help auditors in determining what combinations of strengths or weaknesses are acceptable or unacceptable for reliance on internal controls. They also contend that there exists little research on internal controls, especially as reflected in SAS No. 55. Felix and Niles advocate continued research in the area of examining the sufficiency and quality of combinations of controls.

The most current internal control literature includes the report by the Committee of Sponsoring Organizations of the Treadway Commission ("COSO" report) of 1992. This report consists of an Internal Control Integrated Framework which identifies five criteria for an effective internal control system. These components are: a) the control environment; b) risk assessment; c) control activities; d) information and communication; and e) monitoring.

The COSO report espouses that when the five criteria are met, an effective control system exists. The report also maintains that the five components are multidirectional in their interaction with each other, although no suggestion is made as to what the interaction effects might be.

COSO defines internal control as a process to ensure that reasonable assurance is provided for achieving objectives. Achievement of objectives fall into three categories:
1. effectiveness and efficiency of operations;
2. reliability of financial reporting; and
3. compliance with applicable laws and regulations.

Internal control can be viewed as being relevant to a part of an entity or to the entire entity taken as a whole. COSO can be used to focus on either this partial or overall aspect of control.
Ashton and Brown (1980) contend that if one desires replacing human decision makers with models, then experienced subjects should be used for such modeling. This approach results in increased judgment insight and judgment consensus. Their experimental results suggest a 78% predictable variance in subject judgments. This result is consistent with other accounting researchers' results (Ashton (1974) and Ashton and Kramer (1980)). Ashton and Brown contend that the unexplained variance in all the studies is the result of subjects' nonsystematic response patterns.

Ashton (1986) examines the question of how many experts and which experts are necessary to maximize validity of a judgment task. Based on Hogarth's (1978) analytical model, Ashton determines that group validity converges at ninety-three percent when thirteen experts are considered. Hogarth's model suggests that:

Group validity is an increasing function of the number of experts and their mean individual validity, and a decreasing function of the mean intercorrelation among the experts' judgments.9

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9 Robert H. Ashton, "Combining the Judgments of Experts: How Many and Which Ones?" Organizational Behavior and Human Decision Processes Vol. 38 (1986), p. 406.

Hogarth's model assumes that a rank ordering of alternatives is possible, given the judgmental task. This assumption is necessary since the model relies on a correlational measure of validity. Assessment of internal controls by expert auditors possesses this task characteristic. Consequently, it is reasonable to rely on Ashton's results of achieving high group validity with a maximum of 13 respondents.

Both the professional standards and the COSO report recognize the involvement of external auditors in the process of designing, maintaining, and evaluating internal controls. For example, the Codification of Statements on Auditing Standards is specifically designed for professional guidance in external audits, including the understanding and evaluation of internal controls. External auditors use such guidance in their day-to-day auditing activities.

COSO recognizes the external auditor as the most important external party in helping an entity achieve its control objectives. Auditors communicate audit findings and make recommendations for corrective action. They also communicate deficiencies in the internal control system and recommend improvements to the system. These activities and communications to the entity relate not only to financial statement reporting, but also to compliance with regulations and efficiency of operations.

These tasks performed by external auditors make them ideal subjects for making assessments on internal controls within the COSO decision framework.

Methodology

The research approach encompasses an empirical study. The treatment variables include the five categories identified by COSO to be elements of a system of internal control as independent variables and a series of overall internal control assessments of those independent variables as the dependent variables. Experimental results are measured by examining the classification accuracy of a neural network.

Hypotheses Development

The research question to be answered is to what extent do internal control assessments developed by a trained neural network model differ from those of an experienced auditor? The researchers developed the hypotheses from the three areas of the COSO framework. The following hypotheses are presented in the null.

Hypothesis 1:
Ho: There is no significant difference between the classification accuracy of a neural network model and an expert auditor's assessment of operations internal control effectiveness.

Hypothesis 2:
Ho: There is no significant difference between the classification accuracy of a neural network model and an expert auditor's assessment of financial reporting internal control effectiveness.

Hypothesis 3:
Ho: There is no significant difference between the classification accuracy of a neural network model and an expert auditor's assessment of compliance with rules and regulations internal control effectiveness.

Experimental Design

The experiment involves obtaining assessments of internal controls by external auditors over operations, financial reporting and compliance. The database developed from the auditors assessments is then used as the database to develop a neural network model to make the same kind of internal control assessments as the auditors. Assuming the auditors' database contains a degree of consensus (based on group validity theory of Ashton 1986) the network model is tested by using a holdout sample that is then compared to the auditors' responses. Experimental results are measured by comparing the reliance on controls demonstrated by the external auditors and that of the neural network model.

Decision Setting: Internal Control Assessment

Accountants, audit committees and audit firms often rely extensively on an entity's internal control system. Appropriate reliance on the control system allows an audit firm to minimize subsequent substantive testing in order to render an opinion. The internal control assessment task involves identifying complex patterns of relationships within the control system in order to make an assessment as to the control system's effectiveness. Neural network modeling is ideal for this judgment process. Therefore, a task involving internal control assessment is utilized to demonstrate the capability of a neural network to enhance the accounting information system's ability to provide information useful in decision making.

Decision Framework

To model the internal control assessment process, complex input/output relationships must exist and be identified. Internal control assessments consist of many complex intermediate assessments. These intermediate assessments are used to make final assessments. Assessments involve identifying the state of internal control attributes and the level of assurance provided as to the effectiveness of the control system.

The decision framework in this research is designed to parallel that of the Committee of Sponsoring Organizations of the Treadway Commission (COSO) (1992). COSO provides a normative framework that identifies sets of attributes of the control system (inputs) that are used to assess the effectiveness (outputs) of the control system. Within this framework, COSO has identified five internal controls that determine the effectiveness of the system of controls. These five controls are the independent variables that affect the classification of internal controls as to effectiveness. These five controls are the control environment, risk assessment, control activities, information and communication, and monitoring. COSO identifies effectiveness in three areas: operations, financial reporting and compliance with laws and regulations. The decision framework used to design the instrument consists of the five internal controls as independent variables and the three classifications of effectiveness as dependent variables. This study is concerned with a neural network's accuracy and usefulness as a modeling technique in recognizing patterns

that exist in complex accounting settings.

Subjects

External auditors are utilized as experimental subjects. Since the experimental setting involves auditors' assessments of internal controls, subjects are selected at an appropriate stage in their professional development (greater than four years experience) to enable them to complete the designed task. COSO identifies three categories over which internal controls need to be assessed: operations, financial reporting, and compliance. External auditors are experienced in this type of assessment.

Since the data gathered from the subjects is intended to create a knowledge base useful in training a neural network in assessing internal controls, it is desirable to have as homogeneous a group of subjects as possible for the assessment task. Consequently subjects are highly familiar with the COSO framework. Subjects are experienced in the development of COSO or in subsequent marketing of COSO for their firm. Thirteen external auditors are utilized as subjects in developing the data for the neural network. This number is based on Ashton's (1986) research on the appropriate number of subjects needed to achieve group validity when combining expert judgments. (Manipulation checks are embedded in the experiment to assure reliability of assessments.)

Instrument Design

The experimental instrument is designed to capture the decision making process of subjects. The instrument captures, at a macro-level, internal control effectiveness. The instrument consists of fifty-four control scenarios. Each scenario is independent of the others. Each scenario presents to the subjects, five barometers representing the five independent control variables.[10] These barometers reflect a 15%, 50% and 85% scale, with 0 representing no control and 100% reflecting 100% control for that particular control attribute. Each scenario presents a different combination of controls. The subjects received identical instruments (although each subject received a different randomized version of the instrument).

The five aspects of internal control represent the independent variables in the instrument. The five internal controls describe the process by which reasonable assurance is provided as to the achievement of control objectives.
COSO also identifies three control objective categories. These control objective categories include: operations, financial reporting and compliance with laws and regulations. These three classifications of effectiveness are the dependent variables in the experimental model.

Subjects are asked to assess the overall effectiveness of the internal control system with respect to the three categories suggested by COSO: operations, financial reporting and compliance with laws and regulations. Subjects are asked to make this assessment by indicating a low, medium, or high level of effectiveness. This measurement improves external validity, as auditors usually assess internal controls in this manner. The completion of all instruments took approximately one hour to complete.
Judgment tasks embedded in the typical external audit involve many complex judgment processes on the part of the auditor. It is important to limit the context in which an auditor makes such judgments. According to Gibbins and Wolf (1982):

Judgments, particularly where experts are concerned, are powerfully affected by the way in which judgment tasks are represented, how they are embedded in the world to which the judge is accustomed. Good descriptions of the judgmental environment, therefore, provide important external validity referents for experimental and other controlled research into audit judgments.[11]
The experimental instrument used in this research reflects many of the seventeen predictors of whether problems will arise in an upcoming audit identified by Gibbins and Wolf so as to reduce the ambiguity of the audit environment. They also serve to produce a homogeneous view of the audit environment to the subjects and increase external validity.

[10] Appendix A contains a sample instrument that demonstrates the five input barometers.

[11] Michael Gibbons and Frank M. Wolf, "Auditors' Subjective Decision Environment--The Case of a Normal External Audit," The Accounting Review 57 No. 1 (January 1982), p. 106.

Empirical Results

If a decision maker were to rely on the neural network for predictions of effectiveness of internal controls, prior research (O'Callaghan, 1994) indicates the model would make correct assessments approximately 64% of the time and incorrect assessments approximately 36% of the time. An analysis of the threat of over and under reliance on internal controls is considered in this research.

Assessment of Controls Over Operations

Hypothesis 1:

Ho: There is no significant difference between the classification accuracy of a neural network model and an expert auditor's assessment of operations internal control effectiveness.

With regard to Hypothesis 1, decisions makers who rely on a network model to assess the effectiveness of internal controls over operations would make correct assessments approximately 59.3% of the time.12 Table 1 demonstrates, based on the holdout sample, a) the model's ability to correctly assess internal controls, b) the model's under-reliance on internal controls and c) the model's over-reliance on internal controls.

TABLE 1
Network Reliance on Assessments
Over Operations
(n=103)

	Neural Network Predictions			
Auditor Predictions		Low	Medium	High
	Low	19a	12c	0c
	Medium	14b	31a	4c
	High	0b	12b	11a

a Concurrent Assessments = 59.3%
b Under-reliance Assessments = 25.2%
c Over-reliance Assessments = 15.5%

There were 103 total responses in the holdout sample. Of these, 61 responses were correctly assessed by the model, resulting in a 59.3% correct response rate. Twenty-six responses resulted in an under-reliance by the model in assessing controls over operations (25.2%) and 16 responses resulted in an over-reliance in assessing controls over operations (15.5%). There were no occasions where the model predicted a low assessment over internal controls over operations while the auditor assessed the controls as high. There were no instances where the model predicted a high assessment over internal controls and the auditor assessed the controls as low.

The next two sections present similar analysis of over and under reliance on internal controls over financial reporting and compliance, respectively.

12 Tables 1, 2 and 3 are based on networks somewhat different from 64.1% in that each of the three sections is based on a neural network that examines operations, financial reporting and compliance separately so as to be appropriately compared to a regression model.

Assessment of Controls Over Financial Reporting

Hypothesis 2:

Ho: There is no significant difference between the classification accuracy of a neural network model and an expert auditor's assessment of financial reporting internal control effectiveness.

With regard to Hypothesis 2, decisions makers who rely on a network model to assess the effectiveness of internal controls over financial reporting would make correct assessments at a rate of approximately 68.9%. Table 2 demonstrates, based on the holdout sample, the model's a) ability to correctly assess internal controls, b) under-reliance on internal controls and c) over-reliance on internal controls.

TABLE 2
Network Reliance on Assessments
Over Financial Reporting
(n=103)

	Neural Network Predictions			
Auditor Predictions		Low	Medium	High
	Low	21a	9c	0c
	Medium	12b	37a	3c
	High	1b	7b	13a

a Concurrent Assessments = 68.9%
b Under-reliance Assessments = 19.4%
c Over-reliance Assessments = 11.7%

Seventy-one responses were correctly assessed by the model, resulting in a 68.9% correct response rate. Twenty responses resulted in an under-reliance by the model in assessing controls over financial reporting (19.4%) and twelve responses resulted in an over-reliance in assessing controls over financial reporting (11.7%).
There was only one occasion where the model predicted a low assessment over internal controls while the auditor assessed the controls as high. There were no instances where the model predicted a high assessment over internal controls and the auditor assessed the controls as low.

Assessment of Controls Over Compliance

Hypothesis 3:

Ho: There is no significant difference between the classification accuracy of a neural network model and an expert auditor's assessment of compliance with rules and regulations internal control effectiveness.

With regards to Hypothesis 3, decision makers who rely on a network model to assess the effectiveness of internal controls over compliance with rules and regulations would make correct assessments at a rate of approximately 55.3%. Table 3 demonstrates, based on the holdout sample, the models' a) ability to correctly assess internal controls, b) under-reliance on internal controls and c) over-reliance on internal controls.

Fifty-seven responses were correctly assessed by the model, resulting in a 55.3% concurrent response rate. Thirty responses resulted in an under-reliance by the model in assessing controls over compliance (29.1%) and 16

responses resulted in an over-reliance in assessing controls over compliance (15.6%).

TABLE 3
Network Reliance on Assessments
Over Compliance With Rules
and Regulations
(n=103)

	Neural Network Predictions			
Auditor Predictions		Low	Medium	High
	Low	20a	16c	0c
	Medium	11b	37a	0c
	High	0b	19b	0a

a Concurrent Assessments = 55.3%
b Under-reliance Assessments = 29.1%
c Over-reliance Assessments = 15.6%

There were no occasions where the model predicted a low assessment over internal controls while the auditor assessed the controls as high. There were no instances where the model predicted a high assessment over internal controls and the auditor assessed the controls as low.

Overall Analysis

Research results indicate the networks' ability to not only make a reasonable percentage of correct assessments, but an ability to avoid making a high percentage of extremely incorrect assessments. The network model was never extremely incorrect.
Table 4 presents the statistical analysis of the differences between the network predictions and the auditor predictions in the assessment of internal controls over operations, financial reporting and compliance with rules and regulations presented in Tables 1, 2 and 3, respectively.

TABLE 4
Statistical Analysis of Differences
d.f.=2; alpha=.05

Objective Category	Operations	Financial Reporting	Compliance With Rules And Regulations
Chi-Square	5.041	1.742	31.694*

*Significant difference exists between classification accuracy of a neural network model and an expert auditor's assessment of internal control effectiveness.

As indicated in Table 4, there is no significant difference between the classification accuracy of a neural network model and an expert auditor's assessment of internal control effectiveness in the areas of Operations and Financial

Reporting. There is a significant difference between the classification accuracy of a neural network model and an expert auditor's assessment of internal control effectiveness in the area of Compliance With Rules and Regulations.

Discussion of Results

The potential for a neural network model to assist decision makers in making internal control assessments in the future appears feasible. The results of this research indicate that in the assessment of internal controls over operations, a neural network makes a good decision 84.4% of the time. 59.2% of the decisions on control assessment made by the network correctly match the auditors' assessment and 25.2% of the network decisions would result in the firm's under-relying on internal controls and performing more substantive testing. 15.5% of the decisions would result in over-relying on internal controls over operations. Moreover, no internal control assessment decisions of the network were extremely incorrect. For example, if the auditor expressed a low effectiveness rating over a particular control scenario, the neural network never expressed a high assessment.

In the assessment of internal controls over financial reporting, a neural network makes a good decision 88.3% of the time. 68.9% of the decisions on control assessment made by the network correctly match the auditors' assessment and 19.4% of the network decisions would result in the firm's under-relying on internal controls and performing more substantive testing. Only 11.7% of the decisions would result in over-relying on internal controls over financial reporting. Moreover, less than one percent (.0097) of internal control assessment decisions of the network were extremely incorrect. For example, if the auditor expressed a low effectiveness rating over a particular control scenario, the neural network less than once in one hundred decisions expressed a high assessment.

In the assessment of internal controls over compliance with rules and regulations, a neural network makes a good decision 84.4% of the time. 55.3% of the decisions on control assessment made by the network correctly match the auditors' assessment and 29.1% of the network decisions would result in the firm's under-relying on internal controls and performing more substantive testing. Only 15.6% of the decisions would result in over-relying on internal controls over compliance with rules and regulations. No internal control assessment decisions of the network were extremely incorrect.

Summary

Neural networks provide the accounting profession with an analytic mechanism for assessing internal controls. No internal control assessment decisions of the network developed in this research were extremely incorrect. For example, if the auditor expressed a low effectiveness rating over a particular control scenario, the neural network expressed a high assessment rating only once in 309 attempts (less than .324%). Neural networks provide an excellent paradigm for modeling decision processing of auditors and thereby enhancing their judgment-making ability.

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Part III: International Applications

Competitive Financial Benchmarking Using Self-Organizing Maps[13]

Babro Back, Mikko lrjaia, Kaisa Sere & Hannu Vanharanta

Abstract

Competitive benchmarking is a company-internal process in which the activities of a given company are measured against the best practices of other, best-in-class companies. Internal functions are analyzed and measured using financial and/or non-financial yardsticks. In financial benchmarking, the first step is financial statement analysis to help determine which company characteristics to measure and which yardsticks to apply. However, for the task of running computerized benchmarking systems the amount of financial information required is often so large as to render comparison between companies difficult — or at least very time consuming. The overall objective of this study is to investigate the potential of neural networks for pre-processing the vast amount of financial data available on companies, and for presenting the approximated financial performance position of one company as compared to that of others. The study demonstrates how a large annual reports database on international pulp and paper companies can be pre-processed, i.e. classified with self-organizing maps that is one form of neural networks. The test results are encouraging, and show that self-organizing maps are a viable tool for organizing large databases into clusters of companies having similar financial characteristics.

Keywords benchmarking, company performance, executive support systems (ESS), financial analysis, pulp and paper industry, neural networks, self-organizing maps

Introduction

Competitive benchmarking is an important company-internal process, in which the functions and performance of one company are compared with those of other companies. Financial competitive benchmarking uses financial information — most often in the form of ratios — to perform these comparisons. Financial competitive benchmarking is utilized, among other things, as a communication tool in strategic management, for example in situations where company management must gain approval, from internal and external interest groups alike, for new functional objectives for the company.

Multivariate statistical methods have been used as a tool of analysis for company performance, bankruptcy predictions, stock market predictions etc., although mostly in research contexts. However, many problems have been reported concerning these methods. The two most important problems are the assumption on normality in the underlying distributions and difficulties in finding an appropriate functional form for the distributions. Moreover, results of analyses are difficult to visualize when there are several explanatory variables [Vermeulen et al., 1994].

Many researchers have addressed these problems: Trigeueros [1995] reports on several studies that have shown the existence of positive or negative skewedness in the ratios and on different remedies to overcome these difficulties. He also explains the existence of symmetrical and negatively skewed ratios and offers guidelines for achieving higher precision when using ratios in statistical context.

Fernandez-Castro and Smith [1994] used a non-parametric model of corporate performance to overcome the need for specification of statistical distribution or functional form. Vermeulen et al. [1994] presented a way to visualize

[13] The work reported here was carried out within the AnNet-project. The authors wish to thank the Foundation for Economic Education for providing financial support for this project.

the results with interfirm comparison when the explanatory variable was explained by more than one firm characteristic.

Vanharanta [1995] has used modern computer technology and built a hyperknowledge-based system for financial benchmarking. The system contains a database with financial data on more than 160 pulp and paper companies worldwide. The amount of financial information in this system is, however, so large that it makes comparisons between companies difficult — or at least very time consuming.

> *Artificial neural networks are a promising new paradigm in information processing. Originally, they were developed as computer analogues for the human brain [Hecht-Nielsen, 1991]. Artificial neural networks are able to learn the pattern of a system from a given set of examples; a feature which makes them very attractive. They are applicable to such processes as classification, prediction, control, and inference [Rumelhart et al., 1986].*

The overall objective of this study is to investigate the potential of neural networks, in particular the potential of so called self-organizing maps for pre-processing the vast financial data available on companies and for presenting an approximated position of one company's financial performance compared to that of other companies. By using self-organizing maps we have overcome the problems associated with finding the appropriate underlying distribution and the functional form of the financial indicators. The method chosen also offers a way to visualize the results. This new computer-supported method has previously been suggested by Trigueiros [1995] for use with computerized accounting reports databases, and by Chen et al. [1995] to define cluster structures in large databases.

We anticipate that neural networks do provide new, effective and efficient ways of performing the pre-processing work required in financial benchmarking. The ultimate objective of the ongoing research work, however, is to use artificial neural networks to help executives find company characteristics that will lead to sustainable excellence of a company, in other words to help answer the question: Which are the characteristics that lead a company towards long-lasting good performance? Some company characteristics seem to produce and maintain good overall company performance, sustainable profitability, increasing productivity and continuous growth.

The rest of the paper is organized as follows: Section 2 describes the methodology we have used including the self-organizing maps, the database, the list of companies in the study and the criteria for and the choice of financial ratios. Section 3 presents the results of applying neural networks to the problem and section 4 presents the empirical results. The conclusions of our study are presented in Section 5.

Methodology

Benchmarking

Competitive benchmarking is a company-internal process in which the activities of a given company are measured against the best practices of other, best-in-class companies [Geber, B., 1990]. In the process of competitive benchmarking, internal functions are analyzed and measured using financial (i.e. quantitative) and/or non-financial (i.e. qualitative) yardsticks. Functions measured from one company are compared with similar functions measured from leading competitors, or they are compared with the best practices in other industries. The differences between compared functions are measured. The overall management goal of competitive benchmarking within a given company is to close the measured "gap" by changing the company's characteristics in ways that will improve company performance.
The generic benchmarking process consists of a planning phase, an analysis phase and an integration and action phase. The specific activity of financial competitive benchmarking is an integral part of the generic benchmarking process. In financial benchmarking, the aim is to compare the company with its competitors using available financial information, financial yardsticks. At the beginning of a benchmarking process, in its planning phase, financial benchmarking plays an important role in the identification and selection of the right competitors and/or good performers, those that will act as the benchmarks in the non-financial benchmarking to be done later in the generic

process. Financial benchmarking is also important in the analysis phase when performance gaps are being measured and future performance levels projected. In the integration and action phase, financial benchmarking is useful for monitoring and tracking progress and for re-calibrating the benchmarks. Financial benchmarking achieves its greatest potential, however, as a communications tool at times when company management must gain approval, from internal and external interest groups alike, for new functional objectives for the company, i.e. in strategic management.

The financial information needed for financial benchmarking work is, however, invariably available only from large commercial databases or from specialized reports and publications, from where it must be gleaned with difficulty. Such information is thus far removed from its active users. If the needed financial information is to be brought closer to the active users, it must first be pre-processed, i.e. refined and classified. The overall objective of the present study is to pre-process, with the help of neural networks, the data and information needed for financial benchmarking purposes. Thus pre-processed, the information can be used in computerized benchmarking systems and executive support systems, making the task of competitive financial benchmarking easier and more effective.

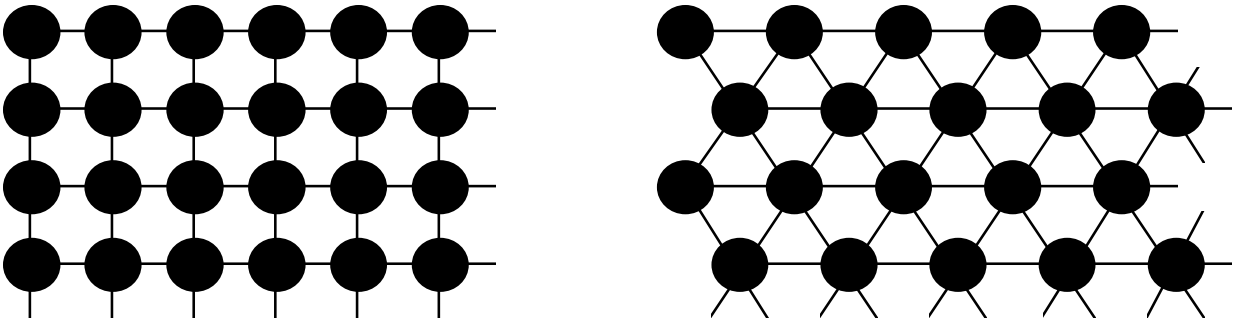
Neural networks

A neural network is a computing device that is able to learn from examples. It consists of a set of simple processing units, neurons, that are connected to each other to form a network topology. A neural network compares input data with output data, and tries to approximate some complicated, unknown functionality between the two. When developing a neural network, the first step is to find a suitable topology for the network and thereafter train it so that it gradually learns the desired input/output functionality. There are two ways to train a network, supervised and unsupervised. In supervised learning the network is presented with examples of known input-output data pairs, after which it starts to mimic the presented input-output behavior. The network is then tested to see whether it is able to produce correct output, when only input is presented to it. In unsupervised learning, the output data is not available and usually not even known beforehand. Instead, the network tries to find similarities between input data samples. Similar samples form clusters that constitute the output of the network. The user is responsible for giving an interpretation to each cluster.

Since companies [in a database] do not have predefined labels describing their financial status, a network intended for pre-processing their data can have no pre-desired outputs. For this reason, we utilize an unsupervised learning method. A Kohonen network [Kohonen, 1995], being the most common network model based on unsupervised learning, is used in this study.

A Kohonen network usually consists of two layers of neurons: an input layer and an output layer. The input layer neurons present an input pattern to each of the output neurons. The neurons in the output layer are usually arranged in a grid, and are influenced by their neighbors in this grid. The goal is to cluster the input patterns in such a way that similar patterns are represented by the same output neuron, or by one of its neighbors. Every output neuron has an associated weight vector. The neighborhood structure of the output layer will cause neighboring neurons in it [the output layer] to have similar weight vectors. These vectors should represent some subclass of the input patterns, thus forming a map of the input space, a self-organizing map (SOM).

The network topology can be described by the number of output neurons present in the network and by the way in which the output neurons are interconnected, i.e. by describing which neurons in the output array are mutual neighbors. Usually, neurons on the output layer are arranged in either a rectangular or a hexagonal grid, see Figure 1. In a rectangular grid each neuron is connected to four neighbors, except for the ones at the edge of the grid. In all the networks we use, the output neurons are arranged in a hexagonal lattice structure. This means that every neuron is connected to exactly six neighbors, except for the ones at the edge of the grid. This choice was made following the guidelines of Kohonen [Kohonen, 1995].



Rectangular lattice Hexagonal lattice

Figure 1

A Kohonen network is trained using unsupervised learning. During the training process the network has no knowledge of the desired outputs. The training process is characterized by a competition between the output neurons. The input patterns are presented to the network one by one, in random order. The output neurons compete for each and every pattern. The output neuron with a weight vector that is closest to the input vector is called the winner. For expressing the similarity between two vectors, we use the Euclidean distance between the two vectors. The weight vector of the winner is adjusted in the direction of the input vector, and so are the weight vectors of the surrounding neurons in the output array. The size of adjustment in the weight vectors of the neighboring neurons is dependent on the distance of that neuron from the winner in the output array.

We use two learning parameters: the learning rate and the neighborhood width parameter. The learning rate influences the size of the weight vector adjustments after each training step, whereas the neighborhood width parameter determines to what extent the surrounding neurons, the neighbors, are affected by the winner. An additional parameter is the training length, which measures the processing time, i.e. the number of iterations through the training data.
Our criterion for the quality of a good map was the average quantization error, which is an average of the Euclidean distances of each input vector and its best matching reference vector in the SOM.

Database and selection of companies

The Green Gold Financial Reports database [Salonen and Vanharanta, 1990a, 1990b, 1991] is used as the experimental financial knowledge base for the neural network tests. It consists of standardized income statements, balance sheets and cash flow statements of 160 companies in the international pulp and paper industry. The database also consists of specific financial ratios, calculated using information from the standardized reports as well as general company information concerning products and production volumes. There are 47 different key ratios for each company. The companies are all based in one of three regions: North America, Northern Europe or Central Europe. The financial data covers a period of five years from 1985 to 1989.

For our experiment we selected 75 North-American and Northern-European pulp and paper companies from the database. Selected companies are listed in table 1. We have also included the averages of Finland, Norway and Sweden as three additional “companies,” bringing the total to 78. The database contained no data on two of the selected USA-based companies for the years 1985-1987. Hence, for the years 1985-1987 there are 76 companies, and for 1988-1989 there are 78. At this stage we excluded the companies of Central Europe as we wanted to include only the most influential countries in the pulp and paper industry.

Choice of ratios

Text-books on accounting provide plenty of financial ratios. However, the large variety of different ratios does not make it easy to find a set of them which would present a company's overall performance. Since there is no unambiguous theory according to which one could define the most informative financial figures, it is obvious that different people consider different ratios as the best. The selection depends usually on empirical results from previous studies, on the analyst's own preferences and, of course, on the purpose of intended use of the ratios. The set of ratios will be different according to whether the intended use is strategic management, bankruptcy predictions or forecasting on the stock market.

Country		Company		
Sweden	3	AVERAGE		
	4	AB Statens Skogsindustrier	11	Norrsundets Bruks AB
	5	Graningeverkens AB	12	Obbola Linerboard AB
	6	Korsnäs AB	13	Rottneros Bruk AB
	7	Mo och Domsjö AB	14	Svenska Cellulosa AB (SCA)
	8	Munkedals AB	15	Stora Kopparbergs Bergslags AB
	9	Munksjö AB	16	Södra Skogsägarna AB
	10	Norrlands Skogsägarens Cellulosa AB		
Finland	1	AVERAGE		
	17	A. Ahlström Oy	25	Rauma-Repola Oy
	18	Enso-Gutzeit Oy	26	Sunila Oy
	20	Kemi Oy	27	Oy Tampella Ab
	21	Kymmene Oy	28	Oy Veitsiluoto Ab
	22	Oy Kyro Ab	29	Yhtyneet Paperitehtaat Oy
	23	Metsä-Serla Oy		
Norway	2	AVERAGE		
	31	Norske Skogindustrier A.S.	34	A/S Union
USA	37	Boise Cascade Corporation	54	Mead Corporation
	39	Champion International Corporation	55	Mosinee Paper Corporation
	40	Chesapeake Corporation	56	Pentair Inc.
	41	Consolidated Papers Inc.	57	Potlatch Corporation
	42	Dennison Manufacturing Company	58	The Procter & Gamble Company
	43	The Dexter Corporation	59	Scott Paper Company
	44	Federal Paper Board Company	60	Sonoco Products Company
	45	Gaylord Container Corporation	61	Stone Container Corporation
	46	Georgia-Pacific Corporation	62	Tambrands Inc.
	47	P.H. Glatfelter Company	63	Temple-Inland Inc.
	48	Great Northern Nekoosa Corporation	65	Union Camp Corporation
	49	International Paper Company	66	Wausau Paper Mills Company
	50	James River Corporation	67	Westvaco Corporation
	51	Kimberly-Clark Corporation	68	Weyerhaeuser Company
	52	Longview Fibre Company	69	WTD Industries Inc.
	53	Louisiana-Pacific Corporation		
Canada	71	Abitibi-Price Inc.	81	International Forest Products Ltd.
	72	Canfor Corporation	82	MacMillan Bloedel Ltd.
	73	Cascades Inc.	83	Noranda Inc.
	75	Canadian Pacific Forest Products Ltd.	84	Noranda Forest Inc.
	76	Crestbrook Forest Industries Ltd.	85	Perkins Papers Ltd.
	77	Doman Industries Ltd.	86	Repap Enterprises Corporation Inc.
	78	Domtar Inc.	87	Rolland Inc.
	79	Donohue Inc.	88	Scott Paper Ltd.
	80	Fletcher Challenge Canada Ltd.	89	Tembec Inc.

Table 1 : The selected companies

In our case the population of ratios is given. It is the 47 ratios in the benchmarking system. These ratios are already organized in the benchmarking system into six groups under the headings:

1) Profitability
2) Indebtedness
3) Capital Structure
4) Liquidity
5) Working capital
6) Cash flow ratios

Our next step was to choose a set of ratios from this population. The choice of ratios in this study was based on an empirical study conducted using ten financial analysts from a large Finnish bank who participated in a validation test of the benchmarking system [Vanharanta et al., 1995]. In the validation test the financial analysts had to deal with issues in the realm of strategic decision-making. If a ratio in that study was used by at least five analysts it was selected as a variable for the network in this study.
This rule resulted in the following nine ratios. The numbers in parentheses indicate the appropriate ratio group number shown above.

- Operating profit (% of sales) (1)
- Profit after financial items (% of sales) (1)
- Return on total assets (ROTA) (1)
- Return on equity (ROE) (1)
- Total liabilities (% of sales) (2)
- Solidity (3)
- Current ratio (4)
- Funds from operations (% of sales) (6)
- Investments (% of sales) (6)

We note that there are four profitability measures, one indebtedness measure, one capital structure measure, one liquidity measure, no working capital measures and two cash flow measures. It seems reasonable that the emphasis is on profitability in a benchmarking situation.

Training and testing the network

In this section we give a relatively detailed description of the construction process followed in developing the self-organizing maps. The actual construction work was performed using The Self-Organizing Map Program Package version 3.1 prepared by the SOM Programming Team of the Helsinki University of Technology.

We started by standardizing the ratios in the database using histogram equalization [Klimasauskas, 1991] in order to ease the SOM's learning process and to improve its performance. Histogram equalization is a way of mapping rare figures to a small part of the target range and spreading out frequent figures so that it becomes easier for the neural network to discriminate among frequent figures.

We constructed three different SOMs. The first and second maps contained data from year 1987 and the third map contained data from years 1985-1989. All the maps were trained in two phases. The purpose of the first training phase was to order the randomly initialized reference vectors of the maps to "approximately correct" values. During the second phase the maps are "fine-tuned," i.e. final ordering of the reference vectors takes place. Training of maps like the first SOM is very fast due to the small amount of training data available (see next section). Furthermore such maps enable comparisons between the financial situations of companies to be made. However, this approach does include the presumption that the input space for each year contains an adequately comprehensive description of the whole possible input space, i.e. all the realistically possible combinations of financial ratios.

The first SOM

The purpose of SOM 1 was to construct a network that could be used in one company to position one or several other companies not yet included in the network.

The histogram-equalized data from 1987 was randomly divided into training (37 samples) and testing (39 samples) data. The size of the map was set at 15 x 10 neurons simply by making several prototypes of the SOM and selecting the one that seemed to be the most appropriate. Too small a map packed the companies so tight that it had no value as a visualization tool, and too big a map spread them around too much, dissolving some clusters.

In the first phase, the learning rate was set to 0.05 and the number of training iterations to 1000. Neighborhood size was set to a relatively high initial value (10) to achieve global ordering. The learning rate function type was chosen as linear, which means that during learning the learning rate decreases linearly from its initial value to zero (in both phases). Also during both phases the neighborhood gradually decreases from its initial value to one.

In the second phase the training length for the best SOM was 25 000 iterations. The optimal learning rate was found to be 0.02. Neighborhood size was tested from 2 to 5 and was finally set at 3.

The initial values for reference vectors were selected randomly, which caused the map to be different each time, i.e. the positions of the companies were not stable in the sense that a certain company would always have been located in the same place on the map. This problem was solved by defining a single benchmark — International Paper Company (IP). This company was selected due to its reputation as a model example of a good company. IP was added to the training data and it was weighted and fixed. Weighting an input vector has the same effect as if it were duplicated — a desired number of times — in the training data. Fixing an input vector has the effect that learning always takes place as if the fixed input vector were matched with a predetermined neuron regardless of the neuron with the most similar reference vector. This did not eliminate the movement of the companies, but it fixed a rotation point at the center of the map. Due to this it was considerably easier to see the formed clusters of companies.

To find all the parameters we constructed several maps. The best map is shown in Figure 2. Eight different groups of companies can be identified (A-H) based on the weight distributions of the maps. These groups are further analyzed in section 4.

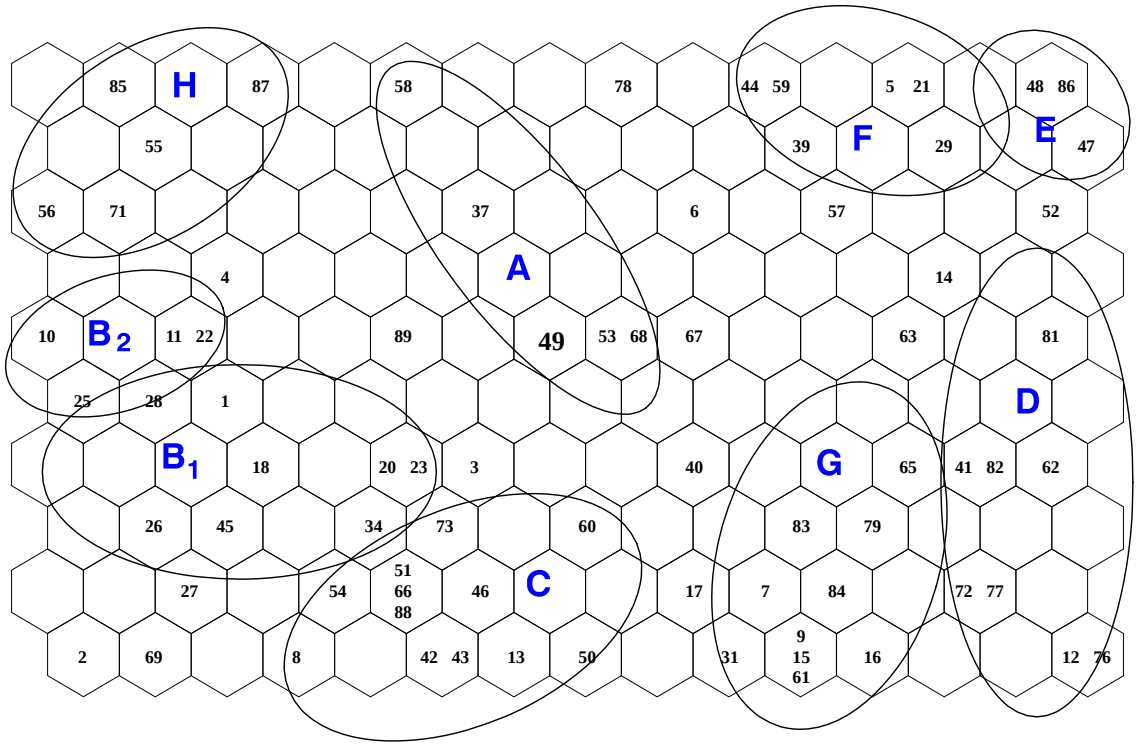


Figure 2 : SOM 1

The second SOM

The purpose of the second map was to test whether the first map had correctly clustered the companies, so this map was trained using all of the data from 1987. The dimensionalities of the map, the structure of the lattice, the learning rate function type and the neighborhood kernel were the same as with the first SOM. The training length was 1000 iterations in the first phase and 95 000 iterations in the second phase. The resulting SOM 2 is shown in Figure 3.
An interesting characteristic of SOM 2 compared to SOM 1 is the fact that IP, which was selected to be the benchmark in SOM 1, almost always situated somewhere close to the center of SOM 2. It required neither fixing nor weighting as was the case with SOM 1. This SOM was also more stable in the sense that there was much less rotation of other companies with respect to IP, or any other company for that matter, i.e. certain clusters always seemed to be located in the same places. This is due to larger training data.

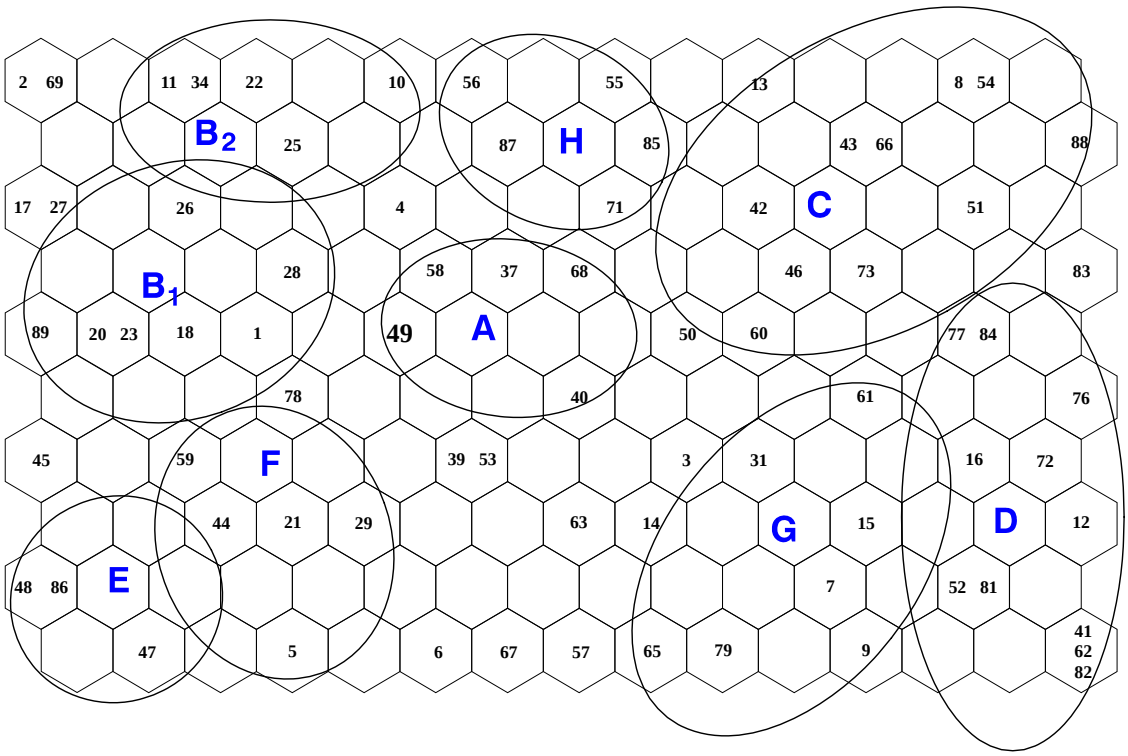
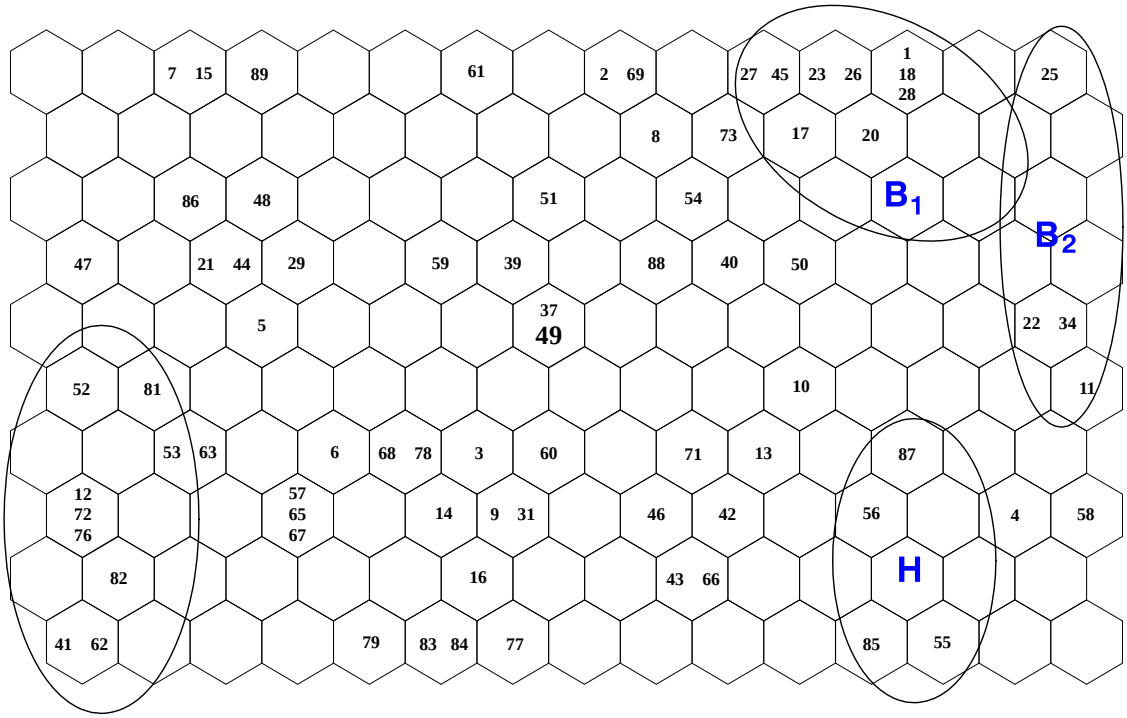


Figure 3 : SOM 2

The third SOM

The purpose of the third map was to test whether the companies, previously clustered for 1987, would be clustered in the same manner regardless of the training data used. This time the whole database was used. It was divided into testing and training data so that the training data consisted of the vectors of all the companies from each of the year 1985, 1986, 1988 and 1989, and the testing data consisted of the vectors of all the companies from 1987.

The dimensionalities of the map, the structure of the lattice, the learning rate function type and the neighborhood kernel were again the same as with the first SOM. Also the appropriate values for all of the processing parameters excluding the training length in the second phase were found to be the same as before. Training of this map required 80 000 iterations in the second phase. The resulting map is shown in Figure 4.


7 15
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> *muddled together and* you *do not actually work through things in that sort of sequence. Trying to describe the logic of your thought process is not very easy because you do not go about it that way.*

However, this was overcome through a combination of the absence of a set completion date and the adoption of three maxims that were observed throughout the project - keep it:

SIMPLE (in scope and application),
FLEXIBLE (to allow infinite refinement), *and*
FOCUSED (limited number of experts and limited number of those who were aware of the development).

A paper-based repertory grid approach (Turban, 1992) and in-depth interview approach was adopted for the process of knowledge elicitation. Iterative prototyping on the knowledge elicitation incorporated the developers' resolve to restrict themselves to one logical view of how things were done, use that as a core, and then develop and refine it. The refinement involved the expert in redefining the processes involved and, where available, obtaining the views of other experts on the appropriateness of the statement of expertise. In effect, the expertise was collected at a fairly broad level and then refined and broken-down to generate detail where appropriate.

One of the major contributors to the power and success of COMPASS was the expert's increasing awareness of his own expertise, and of the implications of this meta-cognition for the lending assessment process:

> *I keep wanting to do more things because I can now recognize how ...* [COMPASS] *... can do more things.* ***Commercial risk*** *is a perfect example of something that, as a bank, we did not do very rigorously because we did not actually have any methodology for doing it. As the program has developed we have recognized that we actually have the processing capacity and the information requirement to enable us to do it properly, much more rigorously than we had ever thought of doing on a manual basis. There are quite a number of examples like that where the imagination is running far ahead of programming....*

Another was the willingness of the knowledge engineer to question all assertions made by the expert and the willingness of the expert to accept he might be wrong. It ensured that nothing was incorporated within the knowledge base without first being examined and validated.

> *It is quite a threatening process, somebody coming along and demanding that you articulate expertise, because none of us are supremely confident in what we do. Life is about convincing yourself as well as others that you are actually competent. So the challenge of someone coming along and saying "so you really think that you are good at this - then articulate it" is difficult to respond to objectively. It is quite difficult for someone to challenge an "expert's" expertise in a way that minimizes the sense of threat, makes you feel at ease, and allows you to work through it and, in fact, learn.*

> *I remember being told that initially it would be a learning process, getting the knowledge out and into the system's structure; and I said "don't be ridiculous, I know what I am doing". But, in fact, that is the way it has turned out. It does improve the way you are doing your job. You do learn because it suddenly hits you that you have not been doing things properly. Bank lending is not a branch of knowledge that is defined, it is not taught in a systematic way. There is no right or wrong way of doing it. Within the banking industry it has always been regarded as a bit of an art - which, some would argue, has been a good excuse for people not actually determining what the rules are. And there is quite a lot of judgment involved in actually identifying and distinguishing those areas where you do need judgment from those where what you need is information and analysis and relevance.*

The knowledge engineer's banking knowledge came from the elicitation process, which helped him to detect inconsistencies that another loan officer may have overlooked. There were disadvantages, but these were largely terminological - the 'current ratio', for example, had to be explained at length.

In the opinion of the developers, had they not allowed sufficient time for the knowledge to be fully elicited, the system would have been significantly less successful, perhaps to the point of being incapable of effective use.

Financial costs and benefits

Use of COMPASS has resulted in major improvements on bad and doubtful debts, increased efficiency in loan processing, less cost, improved loan structuring and pricing in relation to risk - all integral factors in contributing towards extensive financial benefit. It is anticipated that the cost savings generated by COMPASS over the coming years will provide the *Bank of Scotland* with a major edge over its competitors. (Goodall, 1994)

Non-financial benefits

COMPASS imposes control over the loan officers, yet it gives them greater freedom through increasing the level of loan facility they are permitted to grant without reference to Head Office. It also frees a significant amount of their time and it has already been found to be a very effective training device, loan officers having been seen to alter their thinking and general approach to lending as a result of using it.

It is not only the loan officers who have more time available as a result of using COMPASS, Head Office staff also have more time for other activities. In addition, the work Head Office now performs on individual applications is much more focused on the important issues.

Bank of Scotland customers have benefited from the significantly improved speed of response to requests for borrowing - half-an-hour as compared to a week - which the Bank perceives as being likely to enhance its reputation and lead to increased business.

Changes in *Bank of Scotland* lending policy are now automatically incorporated into all lending decisions. Related to that, the greatest benefit for the bank has been the consistency in decision making that has resulted from COMPASS providing decision support at all levels of the credit appraisal process.

A COMPASS consultation

(See Figure 3.) Upon receiving a loan application, the loan officer accesses COMPASS and enters the customer details. Information on the company structure, security, and existing borrowing is entered, along with account information down-loaded from the mainframe link. The audited, management and projected accounts of the customer are also accessed - a seven year span is maintained, three years historic, the current year and a three year projection. If the loan applicant is a new customer, COMPASS helps the loan officer to identify the customer's industrial sector from a choice of 17 primary sectors that subdivide into a total of 84 secondary sectors.

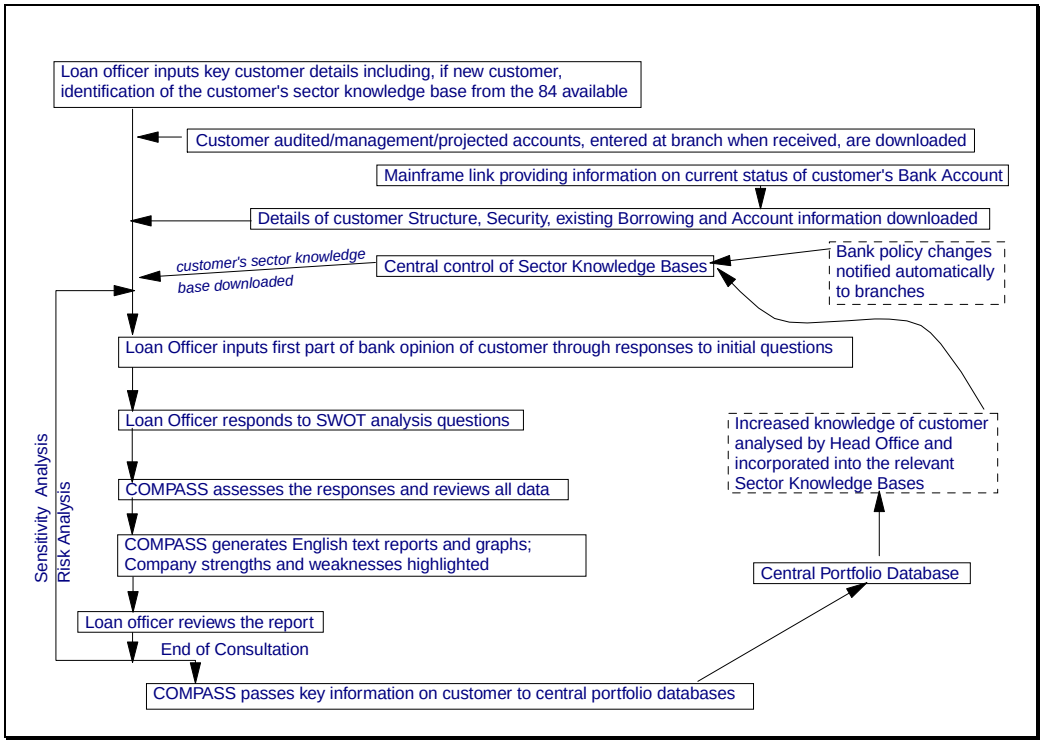

Figure 3: The COMPASS consultation process

At this point, COMPASS accesses the appropriate sector knowledge base and takes the loan officer through the details of the proposal - what is known about the company, what the lending is for, and for how much, etc. These questions have a variable format ranging from simple 'yes'/'no' responses (e.g., 'has the board of directors changed in the last three months?') to five-point Likert scale responses.

It then administers a *Strengths*, *Weaknesses*, *Opportunities* and *Threats* (SWOT) analysis comprising a series of structured sector-specific questions that pass through the three key modules of *viability*, *safety*, and *credentials*. All these questions require responses on a five-point scale, running from one to five. There is also the option to give a 'zero' response where the loan officer does not know the answer. (See Figure 4.) The SWOT analysis comprises a maximum of 70 questions, up to 14 on each of its five dimensions - Market, Sales, Management, Process, and Product. The questions and the number of them asked depend upon the customer's sector environment.

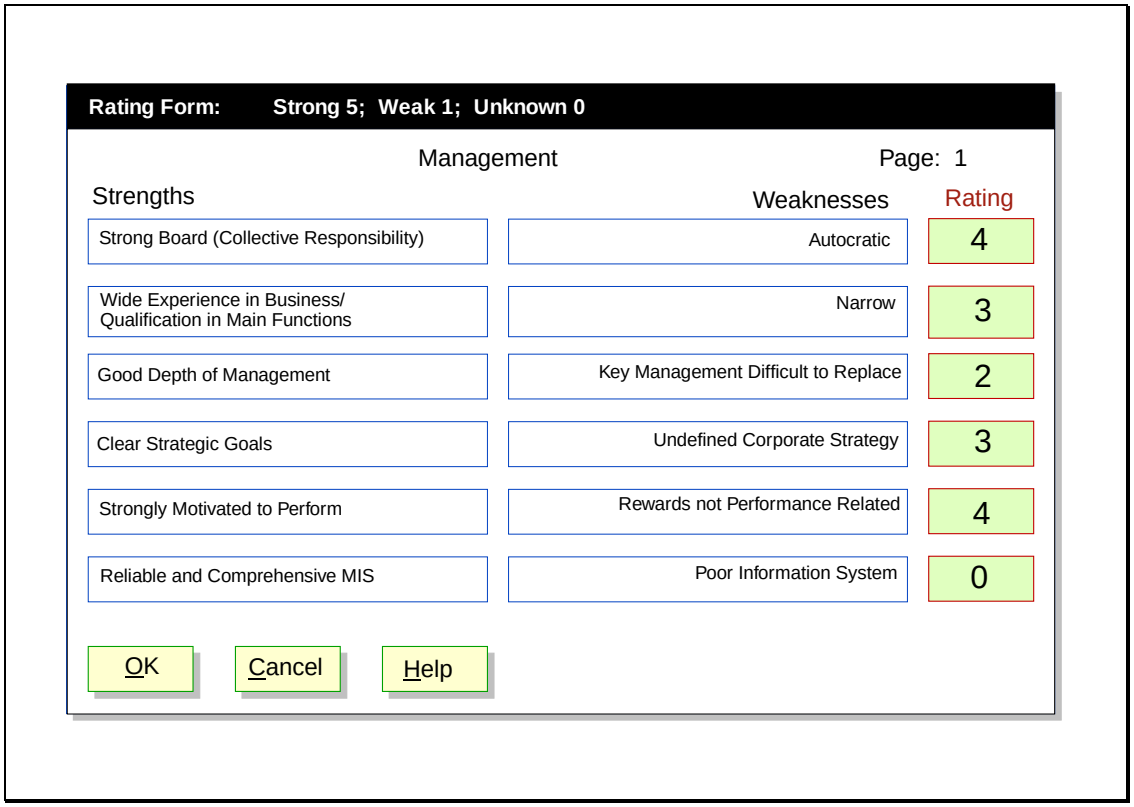

Figure 4 Example of a Completed Management SWOT screen

COMPASS takes the responses to these questions and analyses them in order to assess the strength to place upon the loan officer's opinions, largely from the frequency of 'zero' and 'midpoint' responses. The weighting derived is then applied to the qualitative data and the resulting analysis is then combined with the quantitative data, all in the context of the customer's sector environment. Scale fluctuations between loan officers are being monitored (as part of the iterative prototyping approach that has been maintained following the move from development to implementation) and, should any significant scale effect be identified, the heuristic will be amended accordingly.

Immediately upon completion of the interaction with the loan officer, COMPASS finishes its analysis, informs the loan officer of the strengths and weaknesses of the lending situation, and suggests the terms and conditions upon which lending ought to be granted, if at all. The advice incorporates the Bank's lending policy (in terms of pricing, conditions, etc.). In addition, it indicates the areas that the loan officer should monitor, based on its knowledge of where the risks are coming from.

COMPASS does not tell the loan officer what to do. The output is designed to highlight strengths and weaknesses of a lending situation. If the situation were particularly strong, COMPASS would recommend lending. If it were very weak, it would recommend against lending. For the bulk of situations that are neither very strong nor very weak, it indicates where they are strong, and why, and where they are weak, and why. It highlights the risks, explains why they are risks and quantifies them, both in terms of the likelihood of occurrence and the movement required in order to eliminate them. This offers the possibility of an enhanced, more informative, more supportive service to customers. However, COMPASS has not been in use for a sufficiently long period to detect whether this has occurred.

The strength of COMPASS compared to more traditional approaches lies in its handling of these situations where, for example, there may be weak *viability* and weak *safety*, or weak *credentials* and strong *viability*, or some other unbalanced combination. It not only identifies weakness, but it knows the extent of the weakness - i.e., the boundaries within which the risk exists. Under the more traditional approaches, while weaknesses were identified, there was no adequate way in which to test the limits of the risk. The loan officer had to make a judgment based on imprecise information. COMPASS clarifies the risk situation, making the judgment both easier and more likely to be appropriate.

The loan officer is then able to investigate the various risk aspects, using sensitivity analysis on the customer information data and sector data and, by revising the previous responses to any of the questions that had been presented by COMPASS, rerunning the *viability, safety, and credentials* modules. At any point, the loan officer may exit and request a report, seeing at a glance how the changes made have affected the conclusions drawn. Once the loan officer has completed the consultation, a final report can be generated based on the revised assumptions and responses. As a result, while the final judgment is left with the loan officer (or, if the amounts involved are high, the Bank's Head Office), the decision taken is based on a consistently comprehensive methodology and approach that takes full account of the commercial risks involved.

Conclusions

Expert systems like COMPASS demonstrate the importance of operating beyond the quantitative world of the theoretical *discriminant analysis*, *logistic regression*, and *neural networks* failure prediction models when assessing commercial risk. These models neither represent the reality of how failure prediction is undertaken in the 'real' world, nor address how to prevent risk of loss when the prediction proves to be incorrect - i.e. when a company fails that was not expected to fail. This is not surprising for they were developed in order to determine whether any ratio or group of ratios can be a good indicator of financial distress, rather than to find a model that would accurately predict failure.

Their use as the core of a bank's commercial risk assessment system would be inappropriate. At best they are signposts that have to be interpreted in the context of the environment of the company concerned. At worst, they can be misleading, being based on data that is itself flawed and subjective and open to significant manipulation if not in amount, then in description and classification. COMPASS uses seven years of data to enable trends to be detected and cash flows to be identified, and adjusts the underlying value of assets to their 'true' values before undertaking any financial ratio analysis. It then considers many other qualitative factors together with the financial data in the same manner as a highly experienced lending expert would, looks for signs of impending failure, advises the lending officer of them, and then determines whether the underlying assets make the granting of a loan appropriate. As a result, loans are granted to companies that would not otherwise be granted the facility, loan applications that may have otherwise escaped identification as 'high risk' are detected, and both bank and customer are made more aware of the 'true' position of the customer in relation to potential failure.

As illustrated by the heavy losses on lending incurred by the banks in the late 1980s and early 1990s, the banking environment had become too complex for the loan officer plus quantitative decision support tool approach. Only by producing a computer-based system that incorporated qualitative information was it possible to create a system capable of protecting banks from commercial risk. To date, COMPASS has consistently prevented losses on commercial lending. It represents a new dimension in expert system-based decision support for commercial risk assessment. Its strength lies in the combination of the encapsulation of the generic loan expertise of *the Bank of Scotland's* senior lending officer; a sector-specific knowledge base comprising data and information from all the Bank's customers' management and projected accounts, as well as their financial accounts; and in the recognition that loan application assessment involves two categories of expertise - the generic expertise relevant to all applications (that is encapsulated in COMPASS) and the customer-specific knowledge of the loan officer who has previously dealt with the applicant.

The development process emphasized simplicity, flexibility, focus and occurred at a pace that enabled expertise to be successfully elicited. The result is a highly successful operational expert system for a task that had previously proved impossible to encapsulate within an expert system. Clearly, COMPASS supports the hypothesis that the explanation for the present lack of commercial risk assessment expert systems is due to development-approach-related issues rather than to a lack of appropriate software.

There are many lessons to be learned from COMPASS, not just in banking, but across all domains where deeply buried expertise must be elicited if a truly useful expert system is to be developed. Birts *et al* (1993) for example, suggested that the tasks of financial analysts were an inappropriate domain for use of expert systems technology. Consideration of the manner in which COMPASS, particularly the process of knowledge engineering, was developed may lead to a reassessment of that view.

In a domain as risk aware as banking has now become, COMPASS can only be a precursor of a new generation of decision support. However, the greatest lesson learnt is that knowledge engineering is a non-trivial and highly skilled task that, if accorded appropriate status, can make possible what has previously proved impossible.

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Part IV: Audit Applications

Expert Systems for Audit Tasks- Applicability and Impacts

Amelia A. Baldwin-Morgan

Abstract

While numerous authors have discussed the development of particular audit expert systems or provided surveys of audit expert systems, a comprehensive discussion of the applicability of expert systems to auditing and the impacts of expert systems on audit firms is needed. This article interprets the environment of auditing and its readiness for expert systems development, illustrates the applicability of expert systems to a broad range of tasks associated with an independent audit of financial statements, and recounts the impacts of expert systems used for audit tasks.

Introduction

In 1983, leaders in the field of expert systems predicted that the development of expert systems would impact virtually every knowledge-intensive activity undertaken by humans (Hayes-Roth et al., 1983). In fact, the 1980s witnessed an increasing effort to develop expert systems with applications in auditing. This movement was the result of the increasing complexity of the auditing environment, growing specialization within the auditing profession, lower audit fees, and the successful development of expert systems in other professions (Messier and Hansen, 1989). The application of expert systems technology to auditing became increasingly important as public accounting firms faced expanding competition that requires audits conducted with increased efficiency without reducing audit effectiveness (Hansen and Messier, 1986).

Expert systems are the most commercially successful implementation of artificial intelligence (Crevier, 1993). In 1994, an investigation of literature and vendors uncovered 2,500 expert systems which may represent only a small subset of the expert systems in use. Almost two-thirds of these applications are used in business and industry (Durkin, 1994). Correspondingly, the 1990s confirmed that expert systems are not a fad, but rather an important tool that can, if developed and used properly, be used as part of an audit firm's strategy for surviving an increasingly difficult business and legal environment. Expert systems and related technologies and techniques are used in many phases of the auditing process, particularly as tools of quality control and documentation.

Whether expert systems have proven to be the all-purpose tool that some predicted is still up for debate. The purpose of this article is threefold: 1) to interpret the environment of auditing and its readiness for expert systems development, 2) to illustrate the applicability of expert systems to a broad range of tasks associated with an independent audit of financial statements, and 3) to recount the impacts of expert systems used for audit tasks. The discussion proceeds as follows. First, the nature of auditing as a process is discussed. Second, the current business and legal environment of auditing is reviewed. Third, the applicability of expert systems to audit tasks and problems is addressed. Fourth, the impacts of audit expert systems on audit firms are described. Fifth, the future of expert systems development in auditing is considered.

Nature of Auditing

The nature of auditing is fairly unique relative to other areas of accounting and many other professional tasks. Auditing can be characterized as a process that involves a significant amount of professional judgment and requires experience and expertise.

Auditing as a process

The purpose of auditing financial statements is to
gather and evaluate audit evidence of sufficient quantity and appropriate quality in order to form, and communicate to the users of the financial statements, an opinion on the assertions of management inherent in those financial statements for the purpose of adding credibility to those assertions (Holmes, 1995). This process of auditing is made up of many interrelated tasks including planning, evidence gathering, evaluation, opinion making, and communication. Such tasks require much decision making on the part of the auditors.

In reality, audit firms must complete a separate but important task prior to addressing the audit task. This task is the audit client engagement decision. This involves identifying the pool of potential clients, choosing target clients, investigating those clients (to identify such items as audit risk, business risk and possible staffing requirements), proposing audit services to those clients and preparing the engagement letter. Once this task is complete, the auditing of the financial statements follows (Greenstein and Hamilton, 1995).

Auditor judgment and experience

Obviously, the whole process of engaging appropriate clients and performing audits is complex and involved. One of the most important and difficult to define elements of an audit is the presence and exercise of auditor judgment. Experienced auditors develop a certain amount of expertise that they apply to each successive audit to assist them in the many audit-task-decisions. An auditor may develop judgment in a particular part of the audit process due to frequent assignments or develop judgment applicable to a specific type of client due to extensive work in an industry. No amount of textbook study can create this seasoned auditor judgment in novices.

Environment of Auditing

The environment of auditing can be described for discussion purposes as having two important elements - a business environment and a legal environment.

Business environment

The business environment of auditing has been evolving over the past decade or so to one that is characterized by pressures from many sides. Audit firms must withstand increasing and stiff competition, a relative lack of client loyalty, and a great pressure to provide a very high quality service for a small price.

Audit pricing

The current business environment suggests that audit firms are no longer automatically receiving the once-traditional large audit fees. The increasing competition among Big Six firms and the willingness of clients to use smaller firms has contributed to a downward pressure on audit pricing. Particularly in the first years of engaging a new audit client, firms tend to underprice their services in order to obtain the new client (Simon and Francis, 1988).

Audit shopping

Although firms may acquire new clients by discounting their audit prices, the fact that these clients can be maintained for an extended period does not necessarily follow. Clients know that firms will often offer a substantially lower audit fee in order to attract a new client. Clients, therefore, may engage in “auditor shopping” solely for the sake of price (St. Pierre and Anderson, 1984).

Legal environment

Unfortunately, the tendency to undercut audit competition is an interesting illustration of a paradox of audit firm actions (Greenstein and Hamilton, 1995). During the first few years of performing an audit for a new client, audit firms face an increased risk of litigation and legal liability relative to on-going, long-time clients.

The current legal environment is characterized by record amounts of lawsuits against auditors. Audit firms may spend as much as 20% of their revenues on the costs of litigation. These firms are seen as easy targets by unhappy creditors and investors in the even of a bankruptcy or similar crises. Auditors are always in the path of fire as plaintiffs use the shot-gun approach to litigation, often suing everyone with in throwing distance of the failed business or organization. Witness the recent attacks on the auditor of Orange County, California waged by the county (i.e. the client), who blames the audit firm for the county's financial woes created by risky investments (KPMG, 1995; Lowenstein, 1995). How far can the danger of litigation go? In 1990, the danger was real enough to force one of the largest U.S. firms, Laventhol and Horwath, to fold (Stice, 1991).

Applicability of Expert Systems

The expansion of expert systems applied to audit tasks is a function of the availability and affordability of technology, task and problem appropriateness, and the need for audit process reengineering.

Technology availability and affordability

An important factor encouraging the development of an increasing number of expert systems to audit task is the now wide-spread availability of expert technologies. In the early years of expert systems development, only those with access to powerful computers and knowledge of artificial intelligence languages could develop expert systems. Early expert systems were usually developed using powerful workstations and languages like LISP and PROLOG (Durkin, 1994). Thus, the development of expert systems was not affordable for the vast majority of organizations.
During the 1980s and into the 1990s, the development and availability of microcomputers and easy-to-use expert system shells provided a boon to expert systems development. Today, about two-thirds of expert systems are developed using microcomputers and almost half utilize expert system shells (Durkin, 1994). Expert system technology has become truly affordable.

Task appropriateness

The best problem domains for expert systems are those which are small but important, and have human experts, data, and test cases available for development and validation. Expert systems will be successful if (1) the problem area is well bounded and understood, and (2) human experts are available to explain the knowledge needed for the system. In addition, any or all of the following conditions will make the development of an expert system worthwhile: a shortage of human experts/specialists, a need to preserve experts' expertise, a high cost of expert advice or wrong decisions, critical requirement of expert advice, and routine, detail-dependent decision making (Hu, 1987).

Many auditing tasks meet several of Hu's conditions for these four reasons. First, wrong audit decisions have particularly high costs. External auditors can reasonably expect their actions to be questioned in a court of law, with the possibility of substantial damage awards (Guy et al., 1990). Second, the critical requirement of expert advice is highlighted by examining the definition of auditing.
auditinga systematic process of objectively obtaining and evaluating evidence regarding assertions about economic actions and events to ascertain the degree of correspondence between those assertions and established criteria and communicating the results to interested users (American Accounting Association Committee on Basic Auditing Concepts, quoted in Guy et al., 1990).

Third, auditors are expected to assimilate a lot of detailed information. Fourth, the knowledge and critical experience of the expert auditor cannot be replaced easily, even by well-educated college graduates with newly obtained CPA certifications. A good education and a passing grade on the CPA exam does not instantly provide the auditing profession with new experts.

Based on the conditions and characteristics of the auditing environment, the increasing interest in auditing expert systems and the number of auditing systems that are being developed and implemented is not surprising. Deciding

which audit tasks or problems are best addressed by expert systems is not necessarily a straight-forward proposition. Several approaches to identifying the applicability and appropriateness of expert systems to auditing exist.

Audit task approach

Expert systems can be classified according to the generic problems they solve. One way to identify tasks for potential expert systems development is to classify applications and tasks according to decision type (O'Keefe and Rebne, 1993). Turban (1995) identifies eight generic categories of expert systems that address narrowly defined problems areas. Table 1 illustrates these categories and specific audit tasks they describe. The tasks associated with the audit client engagement decision and the performance of an audit are related to many generic tasks to which expert systems are applied.

Table 1. *Expert system tasks and audit tasks.*

Category	Generic Problem	Audit Client Engagement	Audit Performance
Planning	Developing plans to achieve goals	Identifying potential, target, and undesirable clients	Planning the audit
Design	Configuring objects under constraints	Proposing audit services to a new or continuing client	Planning the audit
Diagnosis	Inferring system malfunctions from observations	Evaluating risk associated with client portfolio	Evaluation of internal control
Monitoring	Comparing observations to plans, flagging exceptions	Investigating potential client	Gathering of audit evidence
Interpretation	Inferring situation descriptions from observations	Evaluating results of investigation of potential client	Evaluation of audit evidence
Prediction	Inferring likely consequences of given situations	Deciding whether to propose audit services to a new client	Going concern and materiality judgments
Debugging	Prescribing remedies for malfunctions	Identifying solutions to high risk associated with the audit client portfolio	Recommending solutions to financial statement problems
Repair	Executing a plan to administer a prescribed remedy	Altering the client portfolio for the purpose of controlling risk	

The applicability of expert systems to the audit process is an accepted reality. Many expert systems have been developed for various tasks that are part of performing an audit. Abdolmohammadi and Bazaz (1995) identified numerous audit performance tasks and sub-tasks that are appropriate for expert systems development.

Critical success factors approach

Havelka and Sutton (1993) also identified task domains for expert systems development. They refined a model of critical success factors to help determine which audit tasks expert systems should address. Table 2 illustrates these critical success factors. Havelka and Sutton (1993) recognized that the audit domain has a unique group of attributes that must be considered an important part of the audit environment and, therefore, should be carefully thought about when considering expert systems development.

Havelka and Sutton's model is a definite improvement over the traditional generic expert system task identification approach. Their approach is unique in its recognition of the uniqueness of the audit environment and the need for specific success factors. However, this approach is still very much focused on audit tasks and not audit problems.

Table 2. *Critical success factors model of Havelka and Sutton (1993).*

Category	Attributes
Audit Oriented Features	Audit community agrees on high payoff System non-disruptive to clients System involves auditor in problem-solving

Task/Problem Features	Task uses a large knowledge-base Task is heuristic Task is divisible Task does not require deep knowledge Task does not require optimal solution Task is difficult, yet teachable Skills difficult to transfer Similar expert systems exist
Expert Features	Consensus can be reached Creativity not required Knowledge loosely organized

Audit process reengineering

O'Keefe and Rebne (1993, p.4) have described the task classification methods of identifying areas for expert system development as "solutions in search of problems." They imply that we must begin with problems that need solving and apply expert systems to those critical problems. Havelka and Sutton (1993) recognized this to some extent in their development of their critical success factors model.

The combination of task appropriateness and availability and affordability of expert system technologies may not be sufficient to motivate the development of expert systems for audit task. Additional critical motivation is provided by increased pressure to cut costs while improving audit effectiveness and simultaneously controlling the business risk of the audit firm. The current situation calls for the application of the concepts of business process reengineering to the audit task.

Business process reengineering is a method of
business process improvement that fundamentally reinvents the way business tasks and goals are accomplished using the most advanced technologies available. Audit firms, desperate to survive in an environment that is both ruthlessly competitive and fraught with litigation and liability problems, continue to consider expert systems important to reengineering traditional audit processes (Greenstein and Baldwin-Morgan, 1995).

This suggests that problems in the audit process should drive the development of expert systems. An example of a problematic audit task that expert systems could profitably address is the audit client engagement task. The fact that this task is a potentially critical problem task is evidenced by the troubles experienced by audit firms in the wake of the U.S. Savings and Loan crisis. However, the tasks surrounding the audit client engagement decisions have seen little expert system development (Gray et al., 1995; Greenstein and Hamilton, 1995). In fact, many models of the audit process ignore this important prerequisite to conducting an audit (Asare et al., 1994; Simunic and Stein, 1987; Huss and Jacobs, 1991). Tasks associated with the audit client engagement decision are included in Table 1. Expert systems may be an important tool for improving this important task and other problem audit tasks.

The important point is that would-be audit expert system developers should aim their skills at developing expert systems that solve audit problems that are of immediate importance in the current audit environment. Therefore, the identification of problem areas may be just as important as, if not more important than, the identification of audit tasks.

Impacts of Expert Systems

Many expert systems have been developed for audit tasks. Audit firms need to have some ideas of the potential positive (and negative) impacts that may result from the use of expert systems. The impacts of such expert systems for audit tasks have been the subject of much prophecy and study. Some articles have hypothesized about impacts based on organizational models, surveys of experts, and personal experience. Others have attempted to directly measure, in an experimental or case study environment, the impacts of real audit expert systems. Table 3 summarizes these impacts of expert systems used for audit tasks.

Studies of potential and future impacts

O'Leary and Turban (1987) hypothesized eight dimensions of expert systems impacts: decision making, organizational structure, centralization/decentralization, organizational effectiveness and efficiency, organizational roles, leadership and power, communications, and personnel requirements. Each dimension was discussed with reference to four basic factors: task suitability, expert systems purpose, expert systems tools and computing environment

Table 3. *Impacts of expert systems for audit tasks.*

	Levels of Analysis			
Categories	**Industry**	**Firm**	**Individual**	**Task**
Efficiency	increase in industry-wide efficiency	firm can accept more audit clients	faster decision time individual can do more work	less supervision is necessary task time is shortened
Effectiveness	audit quality increased	firm-wide consistency	more accurate decisions more problems are handled	more accurate data task consistency
Expertise	enhanced industry expertise	knowledge sharing with-in firm	enhance expertise and judgment *undermine judgment*	shorter learning curve *potential for over-reliance on expert system*
Education	changes in continuing professional education	changes in in-house training	changes in pre-employment educational training	altered task-specific training
Environment	changes in risk of doing audits changes in legal environment of auditing	improved competitive position reduced business risk	changes in job content job satisfaction	task process changed task-specific risk minimized

. Previous literature, interviews and authors' experiences were used to develop exploratory hypotheses.
Summers (1988) theorized about the implications of technological change on auditors. He forecast some rather discouraging results. First, he suggested that expert systems will not impact the auditing profession, particularly in the short term. On the contrary, some impacts have been measured and reported. Second, he believed that the development, introduction, and use of expert systems would result in a shift from labor to capital as a means of covering the costs of hardware, software, knowledge acquisition and expert system maintenance. Third, he forecast difficulties for firms attempting to hire and retain the best auditors, resulting in a professional baseball-like draft system. Fourth, he suggested that firms will begin eliminating the high-risk portions of their practices, in order to appropriately account for the costs of servicing higher risk clients. This fourth prediction may be the most likely to occur since the current legal environment is forcing audit firms to assess the relative risk of their portfolio of clients much more minutely than ever before.

Messier and Hansen (1989) reviewed the state of the art of expert systems in auditing and suggested a number of potential impacts of expert systems on audit practice. First, lower level audit staff will be relieved of many mundane tasks, and be allowed to pursue more challenging work - thus resulting in augmented professional judgment. Second, audit firms will be forced to alter their hiring practices and/or change their entry-level in-house training instruction to address the use of expert systems and the job changes associated with that use. Third, the use of these systems to support audit tasks will result in an audit task that is performed and documented much more consistently than previously. Knowledge of the most experienced and expert auditors will be shared across the firm. Fourth, decisions will be made faster than before because users are more focused on important issues and not spending time on non-relevant tasks.

Murphy and Dorr (1992) described potential social and organizational impacts of expert systems. This was one of the earliest articles to mention a number of negative impacts. Although no empirical investigation was undertaken, existing literature is discussed which could provide models for investigating impacts on the development of expertise, subordination of judgment, and organizational structure. Related theories from a variety of disciplines are discussed and questions for future research are identified.

Baldwin-Morgan (1993) used the Delphi technique to investigate the future impacts on public accounting firms of expert systems used for audit tasks. Developers, users and researchers of audit expert systems answered three consecutive surveys designed to identify which impacts are most likely and most unlikely in the year 2001. Proposed impacts derived from the literature included general and specific impacts on efficiency, effectiveness, expertise, education and external factors. Overall, expertise, effectiveness, and education impacts were the most likely categories of impact (in order of greatest likelihood). Expert systems are likely to impact audit firms in the near future, particular by providing better documentation references, distribution of firm knowledge, and improved decision consistency and quality. Contrary to much of the literature, efficiency impacts were neither likely nor unlikely. Negative external impacts, such as increased risk and dehumanization of auditing were considered unlikely.

Baldwin-Morgan and Stone (1995) reviewed the literature on impacts of expert systems and suggested a matrix model of impacts that can be used to study and compare the impacts of expert systems. They illustrated the use of this model to explain the impacts of two audit expert systems, one used for audit planning and another used to assess tax accruals. Expert systems may have various kinds of impacts (such as efficiency, effectiveness, expertise, education, and environmental impacts) on different levels of the audit setting (such as task, individuals, firms, and the industry).

Sutton et al. (1995) analyzed the legal liability that may result from the use of audit expert systems. They suggested that audit firms must consider the legal liability impact of using a faulty audit expert system and of using an audit expert system improperly. They also suggested that audit firms must consider the potential legal liability associated with failing to use expert system technology. In addition, audit firms must consider the fact that an expert system could be used in a court of law to provide evidence against an audit firm.

Studies of present impacts

Murphy (1990) investigated the impact of expert system use on the development of expertise in novice auditors. The laboratory experiment used senior accounting students as subjects. Non-expert system users outperformed expert system users. This result is contrary to most other similar research.

Eining and Dorr (1991) investigated the impact of an expert system decision aid on novice auditors' experiential learning. Using a cognitive learning theory underpinning, an experiment utilizing upper-level accounting students evaluated four levels of decision aid treatment and two levels of feedback. The groups using expert systems performed significantly better on both accuracy and efficiency than those not using expert systems.

O'Keefe et al. (1993) investigated the work unit level impacts of expert systems in accounting. O'Keefe et al. surveyed developers, sponsors and users of expert systems. The expert systems involved tax, auditing, financial planning, legal, and other accounting-related domains. Concerning productivity, overall results indicated expert system use causes a reduction in supervision, user handling of broader problems, more work performed by the user, improved quality of work, shorter task time, and more decisions that can be made immediately. Results varied by domain; therefore, impacts are dependent on the expert system's task domain.

Abdolmohammadi and Read (1994) investigated the relationship among decision structure and programmability and decision aids in auditing. Using the well known concepts of task programmability and task structure, the contingency relationship among task and decision aid type was explored. A survey of 134 auditors resulted in support for one quarter of the hypothesized task-structure and decision-aid-type relationships. The results provide evidence that questions the relevance of the contingency model to auditing.

Baldwin-Morgan (1994) used the case study method to investigate the impact of an expert system for audit planning on a large public accounting firm. Interviews, questionnaires and archival data provided data relating to the information processing capacity framework, organizational program concepts and potential impacts derived from the literature. Limited impacts were identified on the task process, the firm's information processing capacity, efficiency, decision consistency, documentation, task learning curve, and decision making. The identified impacts were moderated by the user's level of task expertise and the status of the client. Impacts were greater for novice auditors and for first-time audits.

Trewin (1994) investigated the impact of ExperTax on three offices of the national accounting firm, Coopers & Lybrand. The tax accrual and planning expert system is used by both audit and tax staff. Trewin concluded that use of the expert systems improved productivity in data collection, changed job content, increased participation and job satisfaction, enhanced understanding of clients, created firm pride and promoted staff interaction.

Swinney (1995) used a belief-adjustment model to investigate the impact of expert systems use on the judgment of auditors. Practicing auditors participated in the field experiment. Negative expert system explanations were more influential and positive expert system explanations. When explaining loan-loss-research adequacy, expert system explanations were more influential than self-generated explanations. When comparing the actual judgments of auditors to belief revision model expectations, excessive reliance was identified when the expert system output was negative

Summary of impacts

Table 3 summarizes the potential and actual impacts of expert systems for audit tasks that have been reported thus far. Many more expert systems are in use than the limited number that have been studied for impacts purposes. Firms may be reluctant to make their expert systems and results public due to the sensitive nature of such information and the comparative advantages such firms may have obtained from the technology.

Future of Audit Expert Systems

The future of audit expert systems is not certain. Clearly, the indicators are pointing toward even more development of expert systems in auditing. These indicators include the following. First, many audit tasks are appropriate for expert systems development. Second, the business environment in which audit firms operate is increasingly characterized by pressures to cut costs. Third, competition in the audit industry is fierce, often involving underpricing of services to expand the client base. Fourth, the legal environment of auditing is becoming more difficult for audit firms to navigate. Fifth, audit firms are beginning to recognize the need to manage the portfolio of risks represented by their clients and audit engagements. Sixth, the current business environment is one in which many organizations are radically re-engineering their processes to insure their survival.

These pressures suggest that expert system tools and technologies will be even more important to the survival of audit firms who are innovative and prepared to closely scrutinize their audit processes in order to enhanced their competitive position and reduce their legal and business risks. The impacts reported in the majority of studies tend to support these assertions.

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Expert Judgment And Audit Expert Systems: Toward A Discourse Ethic

Jesse F. Dillard & Kristi Yuthas

Introduction

The use of expert systems in audit firms is a small part of a much broader issue concerning technology and its place in our society. The ethical issues raised with respect to expert systems (ES) are a microcosm of those to be addressed concerning the application of technology, especially computer technology. Previous research has focused on a limited subset of the ethical issues surrounding the development and use of audit ES. The issues subset must be expanded if the ethical implications surrounding ES are to be meaningfully addressed. Niebuhr's (1963) cathekontic ethics is enlisted to articulate more clearly the context within which audit expert systems are developed and implemented. Discourse ethics is then proposed as a way of exploring, and possibility resolving, ethical dilemmas. The integration of these two ethical structures at least partially transcends the dichotomies of teleological and deontological ethical theories that have been employed to date.

Despite the increasing level of interest and investment in expert systems by public accounting firms, little attention has been paid to exploring the full impact these systems will have on individuals, firms, and society. This is not surprising, considering the dearth of literature attending to ethical problems relating to other types of information systems (Mitroff and Mason, 1989). It seems likely that experts, public accounting firms, and ES researchers do not consider the implementation of expert systems (or other computer technology) to constitute a moral dilemma. ES research both within and outside the field of accounting focuses largely on describing individual ES, exploring the benefits to be gained from ES, and addressing technical complexities of developing successful systems. The question of whether expert systems should be developed or implemented in particular circumstances is generally a non sequitur relative to the technological could.

A few recent studies have focused specifically on ethical issues associated with audit expert systems (AES). However, this work has been rather reductionist tending to limit the discussion to only a narrow set of issues. For example, Sutton et al. (1995) argue that problems of ownership and liability represent the "basic ethical dilemmas in expert system development" (p. 141). Ownership refers to the rights to specialized audit knowledge or expertise. Mitroff and Mason (1989) suggest that the development of expert systems will cause the profession to address the question of who owns the auditor's knowledge. Before the development of expert systems, expert knowledge resided in the minds of auditors and was carried by the auditors from job to job or firm to firm. When knowledge is incorporated into an expert system, an individual may lose ownership to and control over the expertise.

Specht et al. (1991) address the issue of auditor liability which concerns the question of who is liable when the system fails. These authors conclude that participation in the development and use of an expert system can expose the auditor to increased risk. The expert auditors may be liable for audit failures attributable to the expert system when the knowledge base is found to contain errors or is implicated in erroneous audit judgments.

Sutton and Byington (1993) identify one ethical issue, the ownership of the expertise built into the systems and four epistemological issues: the negative impact of improperly used expert systems, the likely "de-skilling" of the audit work force, the reduced experience level of auditors performing audit tasks, and the potential for extinction of the small and medium size audit firm. Like Sutton et al. (1995), their work focuses primarily on ownership and liability.

It is noteworthy that the "ethical" arguments have as their primary concern economic value and property rights - who has the right to sell what to whom for what price. The implicit assumptions that provide the foundation of such arguments are not examined. The ethics of the market place are not questioned. The legitimacy of the commodification and valuation of human beings is not questioned. The inherent elitism of professional monopolies is not considered. The colonization of the personal, aesthetic and cultural by technique is not considered. It is within a highly constrained context that the question of expert systems in auditing firms is being addressed. The

covering law of the post industrial, late capitalist market place with its reductionist language provides the ultimate foundation for the arguments presented. An analysis of the words and/or phrases used to discuss the "basic ethical dilemmas in ES development" is informative: bargaining chip, contracting, employment relationship, ownership, value, diminished value, ability to negotiate and equivalent level of compensation, increased risk, compensation, ownership, legal liability, matter of business, competitive, contract, negotiation.

The work that addresses perhaps the broadest range of ethical issues in AES is a paper by Dillard and Bricker (1992). Although they do not articulate ethical issues per se, their work has ethical implications for the AES problem. They contemplate the potential consequences of using AES from a number of alternative perspectives and suggest that the views currently held with regard to these systems represent a rationalistic orientation, largely dominated by economic concerns. They explore the problem from a number of perspectives, expanding the discussion to incorporate the subjectivity and quality of work lives of those affected by the system as well as broader structural issues such as unemployment and deskilling. Their discussion also goes beyond the other works discussed above in that it enlarges the notion of the community affected by these systems. Earlier work focused predominantly on individual experts and firms; Dillard and Bricker also consider the effects of ES on the public accounting profession and on society. The following discussion attempts to focus and expand on these ideas.

The purpose of this paper is not to explicate all of the ethical issues associated with AES, nor is it an attempt to prescribe solutions to ethical dilemmas. As we shall argue, this is a serious, sizable and most likely impossible task that can only be adequately pursued through extensive ongoing discourse among all parties affected by these systems. Rather, our purposes are to demonstrate a need to enlarge the scope of the discussion and to introduce two extant ethical theories that can be useful in doing so. The first theory, based on the work of Niebuhr (1963), provides a framework that can be employed in locating actors within a broad range of ethical issues. The second, based largely on the works of Apel and Habermas, provides a set of dialogical, albeit idealistic, guidelines for pursuing moral consensus.

The paper is organized as follows. In the first section, we briefly review ethical frameworks that have been utilized in addressing ownership and liability issues. Probably the most fully developed arguments in AES are presented in Sutton et al. (1995) using deontological, teleological, and contractarian approaches. We suggest that even when the narrow notion of property rights is taken as the basic dilemma, various theories of distributive justice suggest conflicting resolutions.

In the second section, we attempt to provide a means through which these conflicting claims can be understood and debated. We present a discussion of cathekontic ethics following Niebuhr (1963). Niebuhr's work provides a framework for examining ethical issues focusing on the notion of responsibility. In essence, an action is ethical if it appears reasonable when one takes into account the multiple and conflicting responsibilities the actor faces in his or her role(s) as a member of a community.

The third section illustrates how Niebuhr's framework can be applied to the AES discussion. We use the relationship between the expert and firm as an example to illustrate that even within this narrow focus, the range of issues quickly broadens far beyond those previously addressed in the AES literature. Applying Niebuhr's framework to the discussion forces an expansion of the debate far beyond the immediate rights of individuals by recognizing that many parties are affected by the development and use of the ES.

In the fourth section, discourse ethics is proposed as a means for exploring and resolving the ethical issues associated with audit ES. Discourse ethics lays out a theory of how ethical conflicts can be considered. By illuminating the conditions required for morally rational discourse, discourse ethics provides guidelines that can be useful in the ongoing dialogue of ethics in the AES literature.

Distributive Justice

The current AES ethics literature predominately frames the ethical discussion in terms of distributive justice. In this section, the ethical theories relating to distributive justice that have been introduced in the AES literature are briefly reviewed.

The central issue addressed by Sutton, et al. (1995) concerns the "ethics underlying the replication of an expert's knowledge through computer software developed for broad dissemination." (p.2) The ethical issues underlying these considerations revolve around the notion of distributive justice. The primary question is: Who owns the rights to this expertise? Sutton, et al. (1995) present three schools of ethical reasoning, teleological, deontological and contractarian, that shed light on the AES problem. They rightly argue that each of these ethical foundations provides a different perspective on the ethical dilemma being faced by the individual, the firm and/or society with respect to the development and implementation of expert systems within auditing firms. All three of these are evaluated within the current modern economic order which contains the central features of individualism, acquisitiveness and the elevation of the market place to a central social position (MacIntyre, 1984, p, 254).

The arguments are made from the standpoint of entitlements, who is entitled to the expertise acquired and exhibited in an expert system? This position seems consistent with Nozick's (1974) arguments concerning distributive justice. His notion of justice proposes that the rights to what one acquires are derived from how one has acquired it. If property has been legitimately acquired, then its possessor has earned it. Therefore, the person has the right to continue to possesses it and is entitled to any returns generated.

The key is "just acquisition" or a legitimate transfer subsequent to a just acquisition. The question with respect to who is entitled to the use of expert knowledge would hinge on whether the expertise was legitimately acquired without infringing on the efforts or rights of others when the expertise did not heretofore exist, or whether the expertise was transferred from an expert who initially and legitimately acquired the expertise. Nozick states: "The complete principle of distributive justice would say simply that a distribution is just if everyone is entitled to the holdings that they possess under the distribution." (p. 153) In other words, what's mine is mine to dispose of as I wish because I earned it.

The question raised in previous literature on the AES problem is who has earned what? If the issue is that of who was responsible for creating, or earning, the expertise, then under Nozick's proposal, the distributions of the rewards from its exploitation would be fairly easy to settle. Such is the position generally taken in all three of the perspectives addressed by Sutton et al. (1995). The problem with such a position is that there are very few, and in the vast majority of the world there are no, legitimate entitlements. Such a statement is just as valid for intellectual property as it is for real property (MacIntyre, 1984).

As MacIntyre (1981, p. 247) points out, Rawls (1971) takes a different view by grounding the notion of justice in the equity of the claims of each person with respect to these basic needs and the means to meet such needs. Rawls states that

each person is to have an equal right to the most extensive total system of equal basic liberties compatible with a similar system of liberty for all.... [S]ocial and economic inequalities are to be arranged so they are both (a) to the greatest benefit of the least advantaged, consistent with the joint saving principle which provides for fair investment in the interests of future generations, and (b) attached to offices and parties open to all under conditions of fair equality of opportunity. (p. 302)

The first principle takes priority over the second. Liberty is restricted only for the sake of liberty. Justice generally has priority over efficiency. This leads Rawls to the following conclusion: "All social primary goods - liberty and opportunity - are to be distributed equally unless an unequal distribution on any or all of these goods is to the advantage of the least favored." (p.303) These guidelines provide the basis for a rational agent to define a just distribution of goods in any social order.

What if one attempts to use Rawls' principles of distributive justice in considering the expert systems dilemma? How do expert systems affect the primary social goods of liberty and opportunity? And how might the least favored be advantaged? The telling issue here revolves around the needs of the least favored group and the requirement to transfer resources from other groups to this group. Should expert systems be viewed as a commodity for redistribution? Could they be used in divining equitable distributions? The more basic issue surrounds expertise. Is it a social good? Can and should it be commodified? Are there ownership rights to a commodity that requires extensive community investment and expenditure?

As MacIntyre argues, both positions to some extent hinge on the question of who deserves what. One is presumed to be deserving because s/he earned that right. The other is presumed to be deserving because s/he has been deprived. Neither position considers the human community within which the notion of who deserves what in relation to the contributions that are made to the common tasks of that community are constructed. The community provides the context for judgments about virtue and justice (p. 251).

Ethics Of Responsibility

Nozick and Rawls express rival and incompatible social ideals. The consideration of two such theories of justice points out the multiplicity and fragmentation of the foundations within which ethical concepts can be grounded. This fragmentation points to conflict, not consensus, as a fundamental characteristic of modern society and, more detrimentally, provides a pluralist political rhetoric whose function is to conceal the depth of the conflicts.

One might inquire, as does MacIntyre (1984), whether these are actually different perspectives and ask why an ethic cannot be developed that would encompass the apparent contradictions among these foundations. The question then arises as to how to go about constructing a social contract within such a multiplicitous and fragmented context. It seems as though power would dominate the process unless there are some basic rules or guidelines and a means for enforcing the contract. Following from Niebuhr (1963), it is proposed that what is required is a recognition of the communal or narrative nature of ethics and ethical determinations. An ethic of expert systems, and an ethic of technology, cannot be separated from the communal context.

The focus of an ethic is the action response to the question: "What shall I do?" Niebuhr (1963) acknowledges both the teleological and deontological positions, but argues that an ethic must move beyond the atomistic perspectives of these positions.[14] The most common representation is the teleological which sees the "human as maker." The teleological position precedes action with the question: "What is the end?" An alternative representation is "human as citizen" which describes the deontological perspective and precedes action with the question: "What is the ultimate law?" The extension proposed by Niebuhr encompasses both teleological and deontological positions, yet goes beyond them and can be characterized as the "human as responsible self," where action is preceded by the question: "What is going on?" This latter construct is also consistent with, but goes well beyond, the contractarian position proposed by Sutton, et al. (1995). The contractarian position can be viewed as a special case of the deontological view where the "ultimate law" would be treated as the "social contract."
Niebuhr's theory of the responsible self is defined as:

> the idea of an agent's action as response to an action upon [her] him in accordance with [her] his interpretation of the latter action and with [her] his expectation of response to [her] his response; and all of this in a continuing community of agents. (p. 65)

There are four elements in the theory of responsibility: response, interpretation, accountability and social solidarity.

Responsibility is based on the idea that all action is a RESPONSE to previous or anticipated action. A moral action requires awareness and results in a response to an INTERPRETED action representing an intelligence which identifies, compares, and analyzes and relates events so they come into perceived consciousness as understood. Further, one interprets the things that are presented as parts of wholes, as related and as symbolic of larger meanings (also see Murdock, 1992). These larger patterns of interpretation seem to precondition responses to actions. When considering relations among employers and employees one does not only consider the ends each group is consciously pursuing or the self-legislated laws (e.g., social norms or social contracts) the groups are obeying but also the way the groups are responding to each others' actions based on their interpretations (also see Goffman, 1974).

[14]We wish to acknowledge our debt to Dr. Don Utter of Bell Laboratories for pointing out the relevance of Niebuhr to this discussion and sharing his ideas which are liberally drawn upon in the following discussion.

ACCOUNTABILITY refers to the response pattern of one's self-conduct. Actions are responsible not only in so far as they are reactions to interpreted actions upon the agent but also in so far as they are made in anticipation of answers to the agent's answers. The agent's action is like a statement in a dialogue. Such a statement not only seeks to meet, or to fit into, the previous statement to which it is an answer, but is made in anticipation of a reply, looking forward as well as backwards anticipating objections, confirmations, and corrections. The action is made as part of a total conversation that leads forward and has meaning as a whole. Thus an action is responsible not only when it is responsive to a prior deed but when it is so made that the agent anticipates the reaction to the action. So considered, no action taken as an atomic unit is responsible. Responsibility lies in the agent who recognizes his/her accountability for the action, who accepts the consequences in the form of relations and looks forward in a present action to continued reaction.

A fourth element of responsibility is SOCIAL SOLIDARITY. Action is responsible when it is a response to action in a continuing discourse of interaction among beings forming a continuing society. A series of responses to disconnected actions guided by disconnected interpretations would scarcely be the action of a self but only of a series of states of mind somehow connected with the same body. Personal responsibility implies the continuity of a self with a relatively consistent scheme of interpretations of what it is reacting to. By the same token, it implies continuity in the community of agents to which response is being made. There could be no responsible self in an interaction in which the reaction to one's response comes from a source wholly different from that whence the original action issued.

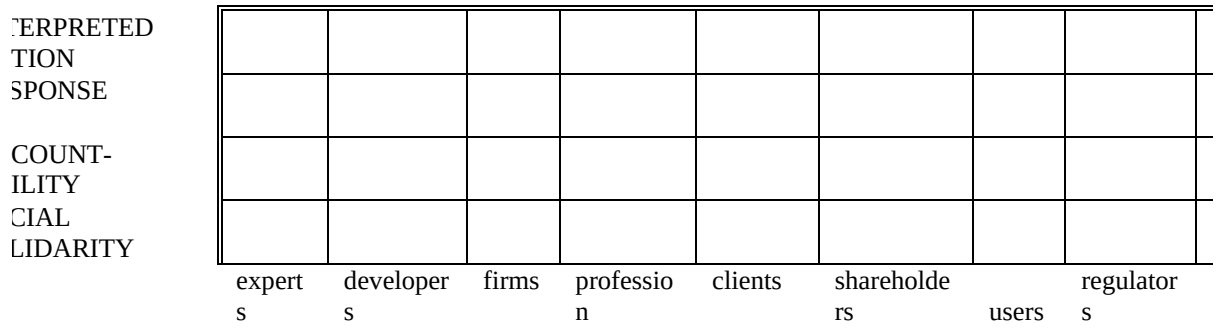
Responsibility In The AES Domain

Participants in the Dialogue

When applied to the AES domain, Niebuhr's work provides insights into the nature of the ethical dilemmas surrounding the development and use of expert systems. It also allows for recognition of the pervasiveness of system-related effects throughout many levels of analysis. For Niebuhr, a determination of what is the fitting action when faced with a decision must consider all parties within the relevant community. In the case of AES, this community includes the expert or experts who lend their expertise to the development of the system, the members of the firm who promote or are involved with the decision to develop and use the ES, the knowledge engineer(s) and other systems personnel who develop and maintain the system, potential current and future users of the system and other firm members affected by it, competing firms and the public accounting profession in general, clients who will be subject to judgments made using ES, shareholders of the client firm, governmental and regulatory agencies associated with public accounting, and other members of society at large affected by the adequacy of the audit.

All these participants in the dialogue of auditing both affect and are affected by the use of expert systems in forming audit judgments. Thus, according to Niebuhr's theory decisions regarding the responsible or ethical use of ES should consider the history of actions and relationships among all these parties. They should consider, as well, the potential future consequences to each group affected by the system. As discussed earlier, these decisions can be characterized using four elements: response (action) , interpreted action (prior actions of other parties), accountability (to other parties subsequent to the response), and social solidarity (nature of the relationships among parties). Applying Niebuhr's framework to the auditing context in this manner results in the framework depicted in Figure 1. Figure 1 suggests that to take a responsible action in this AES context, one must consider the issues from the perspective of each participant in relation to each participant. Only through examining the full complexity of the context and relationships surrounding an action can a responsible action be chosen.

Figure 1



To demonstrate how Niebuhr's framework might be applied to the AES context, we develop an example using one particular dilemma--whether to develop an AES. Of course there are numerous other decisions to be examined, but the development decision is central and provides a rich context for illustrating the framework.

For the AES development decision, Niebuhr's four elements can be interpreted as follows. The response represents the contemplated action. It is a response, rather than an isolated decision, because it takes place within a history of ongoing actions and reactions. For this discussion the response will be defined as the decision to develop, to participate in the development of, or to condone the development of the AES. The interpreted action component represents the nature of the prior interactions among the parties affected by the decision. For example, the expert has a work history with the firm; the profession has provided a service valued by society. Accountability represents the anticipated future actions and responses to the development of the system. In this case, accountability would include expectations about the system's impact on the material and psychological well being, as well as the work lives, of all affected parties. Social solidarity represents the nature of the ongoing relationships among the parties. For example, all parties interact in the sense that they are linked to the public accounting profession in some way and have mutual interests in the continuity and effectiveness of that institution.

Formulating a responsible action in the AES development dilemma necessitates a thorough examination of each box represented in Figure 1. One must attempt to explore the issue from the perspective of each participant in the ongoing dialogue. Only through such an exhaustive undertaking can the ethical landscape surrounding this issue be accurately charted. But under what conditions can such a dialogue take place? In the section on discourse ethics, we present a means through which this project can be undertaken. There we argue that only through extensive, ongoing, open dialogue can these issues be addressed. However, before we consider the complexities of discourse ethics, it is useful to provide an example of how such a dialogue might look if it were to be undertaken.

The following discussion focuses on the relationship between the expert and the firm because they have been the core of prior ethics research in AES, and most ethical issues previously explored have been associated with these two groups. Applying Niebuhr's framework to the AES development dilemma requires that past and expected actions as well as the social context be examined from the perspectives of both expert and firm to determine responsible action.

The Expert-Firm Relationship

We now present an example of how a small portion of the framework might be developed. We base this presentation on a scenario in which one expert and one firm decide whether to cooperate in the development of an AES. We shall assume that in the past the parties have experienced a positive relationship characterized by loyalty and trust and that they expect this relationship to continue in the future. The scenario demonstrates that even within this narrow and idyllic context, the ethical issues that arise extend far beyond those of property and liability previously addressed in the literature.

Figure 2 summarizes the basic elements of the Niebuhr's framework from the perspectives of the expert and the firm illustrating the issues that might arise in a dialogue regarding the AES development project. The issues considered are by no means an exhaustive list of those likely to arise in connection with an AES project; however, they indicate the breadth and complexity of the problem and make it clear that a full exploration of the relevant issues extend far beyond the problems of ownership and liability.

Figure 2: MUTUAL RESPONSIBILITIES OF EXPERT AND FIRM

	Expert	Firm
ACTION	Firm has shown commitment to employee development and job security	Expert has shown commitment to high levels of performance and to tenure
	Firm has continually provided work that is appropriate in nature	Expert has accepted previous changes in the nature of work
	Firm has maintained an acceptable level of audit quality	Expert has performed competent work in prior audits
	Firm has provided agreeable quality of work life	Expert has been satisfied with work requirements and environment
	Firm has dealt fairly with competitive pressures	Expert has accepted conditions necessitated by competitive pressures
RESPONSE	Expert agrees to lend expertise in development of the AES	Firm enlists expert's assistance in developing the AES
ACCOUNT-ABILITY	Participation will maintain or strengthen firm's commitment	Participation will maintain or strengthen expert's commitment
	Participation will not significantly change the nature of expert work for expert or others	Use of system will free expert for other decisions and upgrade capabilities of field auditors
	Use of AES will maintain or improve the quality of the audit	Use of AES will maintain or improve the quality of the audit
	Firm will develop high quality, reliable AES	AES will be technically accurate and will be used appropriately
	Participation will free expert for new challenges	AES will enhance challenges for expert and for field auditors using the system
	Participation will help relieve the competitive pressures facing the firm	AES will enhance efficiency of the audit
SOCIAL SOLIDARITY	Expert and firm have shared responsibility to clients and society, and share mutual concern about the auditing profession	

Numerous ethical issues emerge from within this scenario, and must be addressed to make responsible decisions in developing AES. For example does the firm, by nature of the ongoing relationship with the expert, have the responsibility to provide continued job security? a challenging and non-repetitive body of work? ongoing opportunities for advancement? a high quality audit product? a continually high benefits package? guarantees that

the ES will be used only where its successfulness can be demonstrated? Does the expert, by nature of the ongoing relationship with the firm, have the responsibility to withhold knowledge from competing firms? to continually upgrade expertise? to utilize ES if they enhance audit quality? to accept greater or more narrow responsibilities as tasks are shifted to the ES, to comply with increased standardization resulting from the system? to divulge all available knowledge for incorporation by the AES?

These questions represent only a portion of those which flow from Figure 1 and a much smaller subset of the issues that would emerge from a comprehensive discussion surrounding the responsible development and use of AES. Far more attention is needed within the academic literature and among the affected participants before we can develop a coherent statement of the problems and begin to identify solutions. The following section presents a theory that outlines the conditions under which this discussion of ethical considerations can occur.

Discourse Ethics In Audit Expert Systems

Figure 2 presents a brief sketch of one possible (albeit contrived) description the mutual concerns of a firm and expert in the AES development project. To cultivate a thorough understanding of this dilemma, extensive discussion is necessary. The questions then arise of how the discussion might be undertaken and how it might be judged as to its legitimacy. This section examines the general theory of discourse ethics, and identifies a set of morally relevant constraints that can be useful for achieving ethical discourse in AES.

Discourse Ethics

While Niebuhr's cathekontic ethics can be used to reframe and significantly expand ethical concerns associated with AES, it begs the question of how one engages in the legitimate social dialogue necessary for responsible actions. Discourse ethics is an ethical theory which suggests that moral dilemmas cannot be resolved either through the application of universal ethical principles (deontology) or an analysis of outcomes (teleology). Rather, it suggests that dilemmas are resolved through discussions that consider the multiple perspectives of all parties affected by the decision. The moral course of action in a particular context can thus be arrived at only through consensus among all parties. This consensus can (theoretically) be achieved through fair and rational discourse.

Discourse ethics identifies the types of arguments or validity claims that may be made by these participants and, more importantly, it specifies the conditions under which fair and rational discourse can take place. These validity claims and the conditions for fair discourse are briefly described in the following paragraphs. Following this discussion, we address the problem of achieving these conditions within the context of audit expert systems.

According to Habermas (1984), three basic types of validity claims can be made: truth, normative validity, and sincerity. Participants in a dialogue make claims about the truthfulness of their arguments, about the normative validity or justifiability of particular actions, and about the authenticity of their own subjective points of view. These three claims constitute the basis for all rational discourse. Competence in using these claims is what Habermas calls communicative rationality.

In order to attain communicative rationality and to resolve moral dilemmas through validity claims, certain conditions surrounding the discourse must be met. Validity claims can only result in consensus if they take place in what Habermas calls an 'ideal speech' situation. Ideal speech demands the presence of a number of rather restrictive conditions. Although a wide range of conditions have been articulated in Habermas (1984) and elsewhere, the conditions can be summarized as follows. First, the participants must agree that the purpose of the discussion is to identify truth and thereby achieve mutual understanding. Contrary to situations in which self-interested individuals engage in dialogue as means to achieve personal ends, ideal speech requires individuals to actively seek morally rational consensus. Thus, the goal of the dialogue is not to persuade others to accepts one's own arguments, but rather to obtain consensus from all interested parties through the force of the best arguments.

In order for the best arguments to prevail and formulate a mutual consensus, the communication must be undistorted. To avoid systematic distortion, every interested party must have free and equal access to the dialogue. Everyone must have the opportunity to make validity claims. In addition, these individuals must have equal access to information, rationality and power. Participants must have the opportunity to be fully informed about the dilemma, must have the ability to make rational, unbiased claims, and must be free from force and coercion when

they make these claims. Although these conditions are idealized and counterfactual, they provide useful guidelines for creating and evaluating discursive situations.

Conditions for Morally Rational Consensus

Kettner (1993) summarizes the conditions for undistorted rational consensus by enumerating five morally relevant constraints: generality, autonomous evaluation, role-taking, power-neutrality, and transparency. Each of these conditions is described below relative to the context of AES. It is not our purpose to prescribe how these conditions can be met. We do argue, however, that individuals affected by AES should strive to meet them if moral decisions surrounding these systems are to be achieved. We submit that by acknowledging these conditions, theorists and practitioners will be better equipped to engage in legitimate discourse and to evaluate and resolve dilemmas.

The generality constraint suggests that the dialogue must be open to all interested parties who are competent to participate. To ensure that all voices are heard, the discussion should include as many participants as possible. In the AES context, this constraint suggests that everyone affected by the implementation and use of AES should have the opportunity to express his or her opinions. As discussed earlier, groups affected by AES include, but are not limited to experts, firms, users, developers, regulators, the profession and society.

The autonomous evaluation constraint implies that individuals should be allowed to present their own individual interests and needs. Individuals are not required to seek universalizable ends such as the greatest good, they are allowed to freely express their own interests. These interests are subject to criticism by other participants when, for example, they appear to be irrational or dogmatic. In the AES context, this implies that interested parties should seek mechanisms whereby individuals feel free to state their wants and concerns without fear of repercussion.

The role-taking constraint requires participants to transcend their own positions in the interchange. It implies a kind of Rawlsian thought experiment in which individuals attempt to suspend their own interests and to view the dilemma from the perspective of other participants. In AES, for example, those persons responsible for the decision to develop a system would take seriously the interests of those affected by the system. They must attempt to assume the roles of the other participants and to view the dilemma from, for example, the perspective of the field auditor who will be required to use the system. In addition, they must offer their own interests up for evaluation by other parties. In the AES scenario, participants would position themselves in each box in Figure 1 and attempt to view the dilemma from that perspective.

The power-neutrality constraint suggests that participants must hold positions of equal power with respect to their participation in the dialogue and their ability to express their particular views. This constraint is concerned with coercion from external sources, and suggests that non-distorted communication can occur only when participants are not affected by asymmetric power arrangements. In the AES context, for example, either the firm or the expert may hold power over the other; the expert may be fired or may choose to leave the firm. In actual dialogue between an expert and firm, each may withhold certain statements for fear that negative consequences would result. Dialogue under these conditions comprises strategic or instrumental action, and if a consensus is reached, it will not be a morally rational one. Thus, to accomplish undistorted communication in this setting, it is necessary to develop mechanisms that allow parties to participate without fear of the actions of others. For example, the dialogue might take place under conditions of guaranteed anonymity, or between experts of one firm and partners of another.

The final condition is the transparency constraint. This constraint reinforces the notion that most discourse relates to strategic action, the attempt to use dialogue to achieve ones own self-interested ends. For this reason, to develop rational consensus it is necessary that parties make known to other participants their own individual interests, strategies, and goals. In the AES context, if it is the firm's intention to use the ES as a means of standardizing expert work or of reducing the work force, the firm must make these aims known to other participants. Likewise, an expert seeking to obtain status within the firm or higher compensation, would be required to reveal those objectives. If goals are misrepresented or hidden from others, consensus based on full mutual understanding cannot be attained.

Although these constraints are highly restrictive and may rule out all instantiations of actual discourse, they nonetheless provide ideals which can be sought by those who seek to identify a moral course of action. Firms

committed to understanding and pursuing the ethical use of AES can use these constraints as guidelines for actual conversations. They can seek to include all parties in the dialogue. They can allow and encourage all views and arguments to be expressed. The can attempt to ferret out the arguments most reasonable from the perspective of all participants. They can make their own agendas known. Finally, even though the ideals may be unattainable, the constraints can be used to develop benchmarks for examining and continually elevating the level of discourse actually attained.

Summary And Closing Comments

Prior research on the ethical development and use of expert systems in auditing has focused on a limited set of ethical issues. We have shown how Niebuhr's theory of the 'responsible self' can be used both to broaden the notion of what constitutes an ethical issue, and to provide a framework for identifying what constitutes a responsible or moral action. Essentially, an action is responsible if it takes into consideration previous acts and relationships of all parties affected by the act and anticipates the consequences of the act on these parties. The framework forces those involved in the development of AES to consider how this action fits within the context of the ongoing relationships among experts, firms, the profession, society, and other affected parties.

Discourse ethics provides the means and conditions necessary for implementing Niebuhr's ideas with respect to AES. Discourse ethics suggest that to achieve consensus regarding the ethical development and use of an expert system, the following conditions must exist: all participants must have mutual consensus as a goal; there must be free and equal access to the discussion; and all participants must be appropriately informed, rational, and uncoerced. Although it is unlikely that these conditions can be met in real-life settings, they provide an ideal toward which the discussion can aim and through which real discussions can be evaluated.

The discussion undertaken in this paper represents a preliminary phase in the study of ethical issues surrounding AES. We have shown that the deliberations can, and must, be broadened beyond the current focus on economic claims, in this case rights to intellectual property, and dialogically considered in light of a "responsible self." The debate must consider not only the appropriate action within the context of the legitimate individual entitlement and general covering laws, but also give recognition to the continuing human community, a community wherein the agents will be held accountable for the consequences of their actions by the community. As a result, the self and the community will be more radically defined and continually redefined. The fundamental form of human association is not the social contract into which persons enter as atomic individuals, making partial commitments to each other for the sake of gaining limited common ends or of satisfying certain laws. The fundamental form of human association is rather the face-to-face community in which ongoing commitments are the rule and in which the aspects of every self's existence is conditioned by membership in the interpersonal group.

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Expert Systems and Audit Process Reengineering Applied to Audit Client Engagement Decisions

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Abstract

The current audit environment is characterized by an excessive amount of litigation and auditor liability judgments. Audit firms are being forced to rethink the design of their audit processes. The audit client engagement task is an important part of the audit process that is often overlooked. Improving this task may be the key to controlling audit firm business risk. This paper describes the importance of the audit client engagement decision, the application of expert systems to that process as an example of audit process reengineering, a proposed expert system (ACE) to support audit client engagement decisions, the potential impacts of such a system, and the future of expert systems use as an audit process reengineering tool.

Introduction

The increasing incidence of litigation and lawsuits surrounding auditors and the audit task suggests that now is the time to rethink much of the audit process. A prerequisite task for an audit is the client acceptance/continuance decision, a task that, until recently, has been largely overlooked in much of the auditing literature. Audit firms must consider ways to reengineer the audit client engagement task in order to minimize the risk of litigation while maximizing both auditor effectiveness and firm profits.

The purpose of this article is to describe the need for reengineering the audit client engagement decision process, to identify the role of expert system technology in reducing client risk, and to identify potential impacts on audit firms of undertaking a reengineering of the audit client engagement decision task. First, the next section of the paper discusses client engagement decisions and their role in audit firm strategy. Second, a discussion of audit process reengineering and the role of expert systems in the reengineering effort follows. Third, a proposed research agenda for the ultimate development of an audit client engagement expert support system is described. Fourth, the potential impacts of such a system on audit firms are addressed. Finally, the future of audit process reengineering with expert systems is considered.

Audit Client Engagement Decisions

Although the task of performing an independent audit of a company's financial statements is often discussed in terms of the planning process, audit procedures and the audit opinion, the prerequisite task is at least equally important. That is, the impact of a poor audit client engagement decision may be felt far into the future and could potentially be quite burdensome. Audit client engagement decisions must be discussed in light of their importance to the financial success of the audit firm, their function in the overall audit process, and their role in the organizational strategy of the audit firm.

Importance of the client engagement decision

Litigation and losses affecting audit firms have become common. In 1993 alone, the U.S. Big Six public accounting firms reported over $1 billion in litigation costs - an amount equal to almost 20% of their gross revenues. Almost one-half of this litigation stems from client business distress or failure (Palmrose, 1987). Many of these legal actions are initiated by disgruntled creditors and investors who view the accounting firms as a source of recovery. Even in those cases where the lawsuits are non-meritorious, the accounting firm must expend precious time and resources to reach a settlement. The monumental amount of litigation faced by audit firms in recent years,

particularly in the United States and Europe, suggests that public accounting firms must reassess the audit process (LaFreniere, 1993).

The logical place to begin the reassessment of the audit process is with an evaluation of the client engagement decision. Firms who accept audit engagements with risky clients have learned that those decisions can cost them dearly. Laventhol and Horwath, the seventh largest U.S. public accounting firm, learned this lesson the hardest way in 1990 - the year it collapsed due to monumental liability problems. These recent events indicate that the process of accepting and retaining audit clients must be drastically changed, reengineered to fit the current and future environment in which public accounting firms must operate. Firms that do not radically change the procedures for accepting and retaining audit clients risk a trip down the path blazed by Laventhol and Horwath.

The clients of an audit firm may be viewed as elements of a complex portfolio in which some elements have relatively higher risk and others relatively lower risk (Simunic and Stein, 1990). The current state of auditor litigation suggests that firms have not managed this portfolio of risk very well and perhaps too much variation in clients may exist. In fact, as a step toward better risk management, firms should develop a more comprehensive model of the audit process that includes all of the decisions that lead to the acceptance or rejection of an audit client (Huss and Jacobs, 1991; Cushing and Loebbecke, 1983).

The audit process

The audit process may be modeled in the form of a set of dataflow diagrams, as illustrated in Figure 1. In this model the audit process includes two major phases: the process of choosing the client and the process of performing the audit.

Traditionally, auditors, educators and researchers have focused on the process of performing the audit, not on the process of choosing the audit client. Just as performing the audit involves a number of tasks, choosing an audit client also involves a number of tasks as shown in Figure 2. Any error in this part of the audit process can later result in costly litigation and/or losses for an audit firm.

The practice development task involves identifying the available set of prospective clients (Asare et al., 1994). The process of categorizing potential clients as desirable, undesirable, or unknown is a dynamic process as the firm characteristics, goals and policies of both the audit firm and the potential client evolve over time (Greenstein and Hamilton, 1995). Once the audit firm has identified a potential client and that client is interested in the firm's audit services, an investigation of the potential client ensues.

This investigation will require time and resources and may involve such tasks as meeting with client personnel, researching industry and competition, reviewing financial status, assessing management integrity, accounting practices, and controls, and determining audit staffing requirements. During this investigation process, the audit firm must consider the client's business risk, the audit firm's business risk, and audit risk (Huss and Jacobs, 1991). The best method for controlling the latter two types of risk is to undertake a meticulous and thorough audit client selection process (Walo, 1995).

Big Six firms have widely varying degrees of levels of organizational approval, extent of procedures and documentation, and audit partner knowledge concerning client selections (Huss and Jacobs, 1991). Furthermore, audit partner expertise appears to be applied to client selection without the use of comprehensive and explicit firm-wide procedures (Asare et al., 1994). The process of developing an expert system for audit client engagement support provides an opportunity to reengineer a significant and important part of the overall audit process.

Audit firm strategy and expert systems

Audit firms have long recognized the need to make changes in task processes. Particularly with the advent of information technology, firms have used process change and technology as a strategy for changing the state of the organization (Baldwin-Morgan, 1994). Information technology may be used as a strategy for changing the state of the audit firm, as illustrated in Figure 3.

The current state of the audit firm is assessed according to the audit firm's strategy. The state of the audit firm includes the firm's business risk, legal liability and litigation, the portfolio of audit clients, etc. If this state is not optimal, the audit firm strategy indicates a desire to change the state of the audit firm. This strategy may include audit process reengineering. The audit firm strategy calls for the development of an expert system to be used as a part of the firm's strategy for altering its current state. Characteristics of the firm, such as firm culture and level of innovation, will impact the development and use of expert systems within the firm. The use of expert systems will impact the state of the firm. If the chosen audit firm strategy is suitable, then the state of the audit firm should move closer to the desired state.

Currently, the state of audit firms has been greatly affected by the litigation costs, e.g. Laventhol and Horwath. The organizational strategy of each audit firm must respond with change and move toward improving the state of the audit firm with respect to litigation. While a number of changes in the state of the audit firm are necessary to attain risk containment, the improvement of the audit client engagement/continuance decision is a mandatory objective in the endeavor to control audit firm business risk (Huss and Jacobs, 1991).

Information technologies, particularly expert systems, can assist in reducing the risk associated with the audit client engagement decision and thus improve the state of the organization. Specifically, successful uses of expert systems technology can reduce the amount of gross revenue which goes to cover litigation costs and settlements and help eliminate the negative public image associated with publicized lawsuits. An expert system or expert support system can be used to reengineer the process of the client acceptance/continuation decision task.

Impacts of expert systems for audit tasks

The strategy of developing expert systems has been discussed extensively. Expert systems have been used to reengineer various aspects of many accounting tasks including a number of audit tasks. Expert systems are developed because organizations expect some positive strategic impact on the organization, its processes, and/or competitive position. Accounting-related expert systems have been used to reduce the risk of commercial loan default (Sangster, 1995), increase accuracy of accounting reports (Back, 1992), improve the productivity of credit authorizers (Leonard-Barton & Sviokla, 1988), improve problem solving in financial risk analysis (Fedorowicz et al., 1992) and transform the financial planning process (Sviokla, 1986). Expert systems in accounting have real-world impacts including: reduced need for supervision, a broadening of the tasks and problems handled by users, improved work quality, reduced time on task, and faster decision-making (O'Keefe et al., 1993).

In auditing, specifically, studies of the impacts of expert systems have been undertaken in the laboratory and in the workplace. Expert systems can ensure consistency in audit planning (Baldwin-Morgan, 1994), improve auditor productivity and knowledge sharing (Trewin, 1994) and increase the experiential learning of novice auditors (Eining and Dorr, 1991). While the development and use of expert systems for isolated accounting and auditing tasks has produced many positive impacts (Baldwin-Morgan and Stone, 1995), not all results have been positive. Swinney (1995) suggests that auditors may have a tendency to over-rely on an expert system. Unfortunately, literally all the expert systems developed for audit tasks have addressed tasks that are part of the process of performing the audit, not tasks that are part of the audit client selection process that is the prerequisite for performing an audit. Most of the remaining stages of the audit function are already supported by expert systems (Gray et al., 1991). Thus, the development of an audit client engagement expert system to fill one of the few remaining voids in the audit process should be beneficial in allowing public accounting firms to reap dramatic improvements in this crucial decision making process.

Audit Process Reengineering

Audit process reengineering (APR) involves the application of the tools of business process reengineering (BPR) to the unique realm of the audit process. BPR is a management tool that has been growing in popularity throughout the 1990s.

Business process reengineering

Reengineering, or business process reengineering, is a complex process that involves a search for radically new and innovative methods to accomplish business objectives. According to Peter Drucker, reenginneering has to be done. The key is to start with a clean slate. That is, unlike most change efforts which seek to change existing processes, reengineering involves designing completely new processes. Instead of improving old processes, reengineering starts with an objective (e.g. the desired future state of the company) and creates processes that will shape the company to that vision (Stewart, 1993).

The reengineering process requires the organization to use the power of modern information technology to radically redesign [its] business processes in order to achieve dramatic improvements in their performance (Hammer, 1990, p.104). The purpose is to break away from the old rules, the old technology, the old organizational structures, etc., which were created in the past in a different competitive and technological environment.

The current legal environment surrounding audit engagements is so troublesome for public accounting firms that radical change is required. A reengineering of the audit process is needed to prepare audit firms for the legally and technologically transformed audit environment. Expert systems can be an important technology for aiding in the reengineering of the audit process and its most important primary decision phase, the client engagement decision.

Role of ES in APR

Expert systems have been used to support many phases of the audit process (Gray et al., 1991). Audit process reengineering can only be successful if the benefits and strengths of advanced information technologies are an integral part of the reengineering effort. Concerning the client engagement decision task, an evaluative expert system can be designed to assist the audit partner in choosing clients that fit with the firm's overall risk portfolio. In addition, such an expert system can be the means of promoting firm-wide consistency in the client engagement process. The concepts of expert systems and business process reengineering are not new. However, the assertion that expert systems can be, and in fact, have been used to transform audit processes as part of an overall audit process reengineering activity should be heeded.

Development Of An Expert Support System

In order to achieve the benefits of more consistent, more reliable, and less risky client selection choices, we propose that a new avenue of research be initiated. Specifically, we propose that reengineering of the client acceptance/continuance decision making processes occur via the use of an expert support system.

ACE expert system

The ACE-ES (audit client engagement-expert system) is considered an expert support system because the audit partner, and not the expert system, will have the final say in the decision. An expert support system is simply an expert system (a system which mimics the knowledge and expertise of an expert in a narrow domain) that is used to suggest decision outcomes to the decision maker. An expert system is distinguishable from a decision support system, which aids decision makers using data manipulation and modeling, but does not represent the knowledge of an expert nor the ability to solve problems like an expert (El-Nadjdawi and Stylianou, 1993).

Ultimately, the ACE-ES will include both quantitative and qualitative data and analysis. Stice (1991), for example, determined that certain financial ratios, among other quantitative data, are useful for predicting clients with high audit risk. To prove successful, the ACE-ES must achieve both a low type one error rate (risk of rejecting an acceptable client) and a low type two error rate (risk of accepting an unacceptable client). Previous models, such as Stice (1991), have not succeeded in reaching this objective.

In contrast, the development of an expert system involves processes that have not been utilized in this context previously. First, this development requires the acquisition of knowledge from audit partners who are expert at client selection. Second, this expert system will incorporate both quantitative information (e.g. Stice (1991)) and qualitative information about the potential audit clients. An expert system is particularly appropriate for capturing heuristic and qualitative expertise (Koczkodaj et al., 1994). Qualitative information has been successfully incorporated into expert systems in banking used to evaluate business clients' ability to repay commercial loans (Sangster, 1995). This task is somewhat similar to the client engagement selection task. The use of checklists and

weighting of danger signals must also be incorporated into the expert system to achieve a realistic evaluation of business risk (Wallace, 1995; Asare and Knechel, 1992).

ACE Research Agenda

The development of an expert support system to be used in the client acceptance and continuance decision processes will require a progression of research projects guided by a framework. The knowledge engineering phase of the development of the ACE-ES will be the most critical task, and it will need to be performed in a progressive fashion, allowing learning to occur throughout the knowledge acquisition tasks. We propose that three phases be used to develop the final ACE-ES. Each of these phases are discussed below.

Phase I - Clear Reject Decisions.

The objectives of the first phase of research will be to identify the most troublesome "soft issues" and to establish heuristics regarding the *rejection(discontinuation)* of potential(existing) clients. Use of the Delphi technique to gather information and reach consensus about important factors during the knowledge acquisition phase is an appropriate methodology. The Delphi technique is an appropriate research tool for audit settings (Baldwin-Morgan, 1993; Holstrum et al., 1986; Garsombke and Cerrulo, 1984). The Delphi technique involves surveying a panel of experts multiple times. After each iteration, the panelists are shown all results and comments of panelists and asked to respond again (Cundiff, 1985). Three rounds are usually sufficient to achieve stability in responses and consensus (Linstone and Turoff, 1975).

The Delphi panelists should be selected from those partners who are most experienced at client selection in Big Six firms. Panelists who may be most helpful in creating a useful model of client selection decision knowledge are those who have involvement in the client selection process, have expertise in this problem domain, are motivated to participate, and believe in the benefits of developing the expert system (Delbecq et al., 1975). The difficulties of client selection occur in all firms, but are not necessarily identical in all firms. Using experts from each of the big six firms will aid in the development of a comprehensive model of the audit client selection decision process.

Hamilton (1994) suggests that this situation, a multiple-site related-domain problem, calls for the development of a global knowledge model which includes core knowledge, semi-local knowledge, and local knowledge. Client selection knowledge that is applicable to all audit firms is an example of core knowledge. Semi-local knowledge is that part of the client selection expertise which is applicable to an identifiable subset of the audit firms (due to firm culture or client base). Local knowledge, that of one or an unknown subset of the audit firms, must be selected individually by the individual audit firms as necessary (Hamilton, 1994).

Figure 4 represents the planned system development process for the ACE-ES. This development process should be used during the first two phases of the ACE-ES development. Note that the majority of the planned stages of development, steps one through six, involve knowledge acquisition. This is the most important element of developing the ACE-ES expert system. If the knowledge acquisition process is not completed properly, no amount of quality programming and validation work will produce a useful expert system.

During Phase I, the red flag literature and information gained from the interview process should be used to develop a short list of the most troublesome factors. Once a short list is identified, these factors should be examined to determine which factors in isolation and which factors is conjunction with one or two other items would cause the audit firm to reject (discontinue) the potential client (existing client). The red flag literature contains over 60 different individual items (Wallace, 1995). Working with this many factors, initially, would be prohibitively cumbersome and require questionnaires too lengthy to complete, considering that 434 pairs of items are possible, not including the possibility of combinations of three items. A manageable number of items would be between 15 and 20. The proposed strategy would be to first identify those items, which in isolation, would cause the audit firm to walk away from the client. The remaining items would then be paired to determine whether the existence of two factors would cause the firm to reject the potential client. (If 12 items are considered, then the expert panel will need to make 65 comparisons.) Once consensus is reached regarding which pairs are troublesome enough to be

identified as reject situations, then the remaining pairs are extended to include a third factor. The scenarios with 3 troublesome factors can then be examined to determine whether, in conjunction with each other, they are troublesome enough to reject the potential client.

Thus, Phase I focuses on identifying those situations in which the audit firm would *reject*/*discontinue* the potential/existing client. A series of rule-based heuristics should be able to be developed for the reject outcomes identified. These reject scenarios will be viewed as clear-cut decisions. If the questionnaire is properly designed in such a manner that scores can be determined based upon the experts' responses, then *desirability* scores should be able to be calculated for the remaining scenarios where the client would not be clearly rejected.

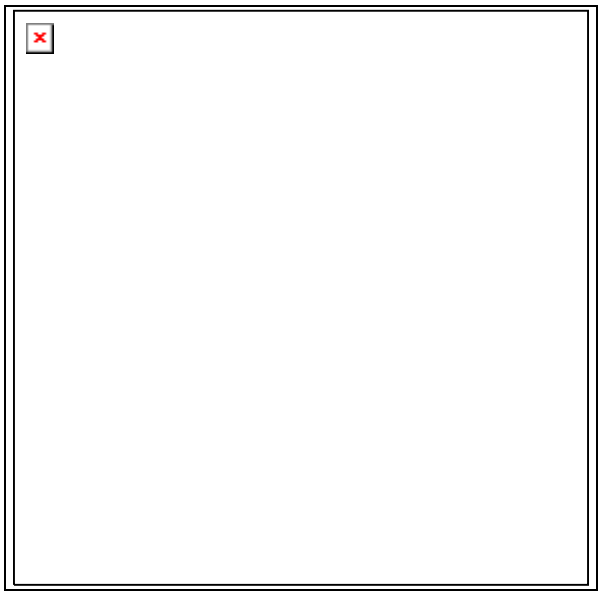
Phase II - Gray Area Exploration.

During Phase II, scenarios which seemed troublesome in Phase I, but did not result in a clear rejection can be expanded to include additional troublesome characteristics to expand the knowledge base. The previous phase should have provided a list of the 15 to 20 most troublesome items and developed rules with as many as three factors considered simultaneously. During this phase, the primary objective should be to develop a rule-based system which develops heuristics incorporating six to seven key "soft issues" simultaneously, as well as financial indicators (going concern analysis). Phases I and II are proposed as separate phases for practical purposes. Consensus cannot be expected to be reached within three to four rounds if too many factors considered simultaneously are included. Once again, the questionnaire should be designed so that a desirability score can be determined for those cases which are not clear "rejects".

Phase III-Determination of Optimal Categorization

. After Phase II is complete, the desirability scores for the gray areas can be studied to determine optimal cut-off points so that recommendations about whether to accept/keep the client or place them on a special risky list may be made. Rules regarding the recommendation to *accept* the client should be made with extreme care. Unlike reject situations, the acceptance of a client ba

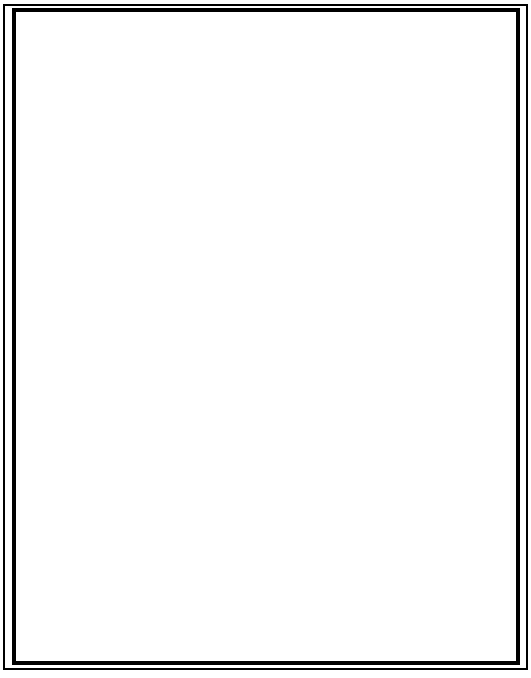
Uncorrelated Entities



Uncorrelated entities also can be captured. For example, resources such as different lines of inventory can be represented as uncorrelated entities. Figure 9 gives an example. Other examples could focus on agents or events.

Parallel Relationships

Parallel relationships occur with the addition of new relationships between entities. For example, new systems such as "just-in-time" inventory systems have changed the concept of inventory. In such systems, inventory may be purchased, but stored at the supplier's location until needed. This is illustrated in figure 10.

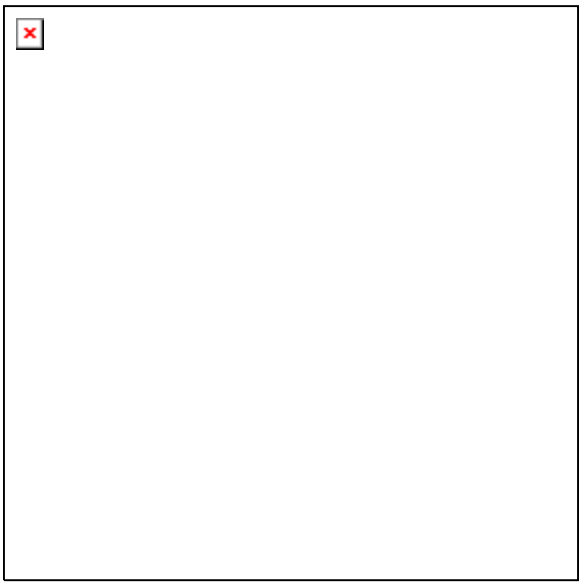


Relationship between Evolutionary Forces and Operations

The evolutionary forces discussed in the previous section are captured in the tasks of this section. A number of examples have been provided that illustrate that the issues evoked in the previous section can be evolved using the tasks generated in this section.

SEAtool- A Tool for Evolution

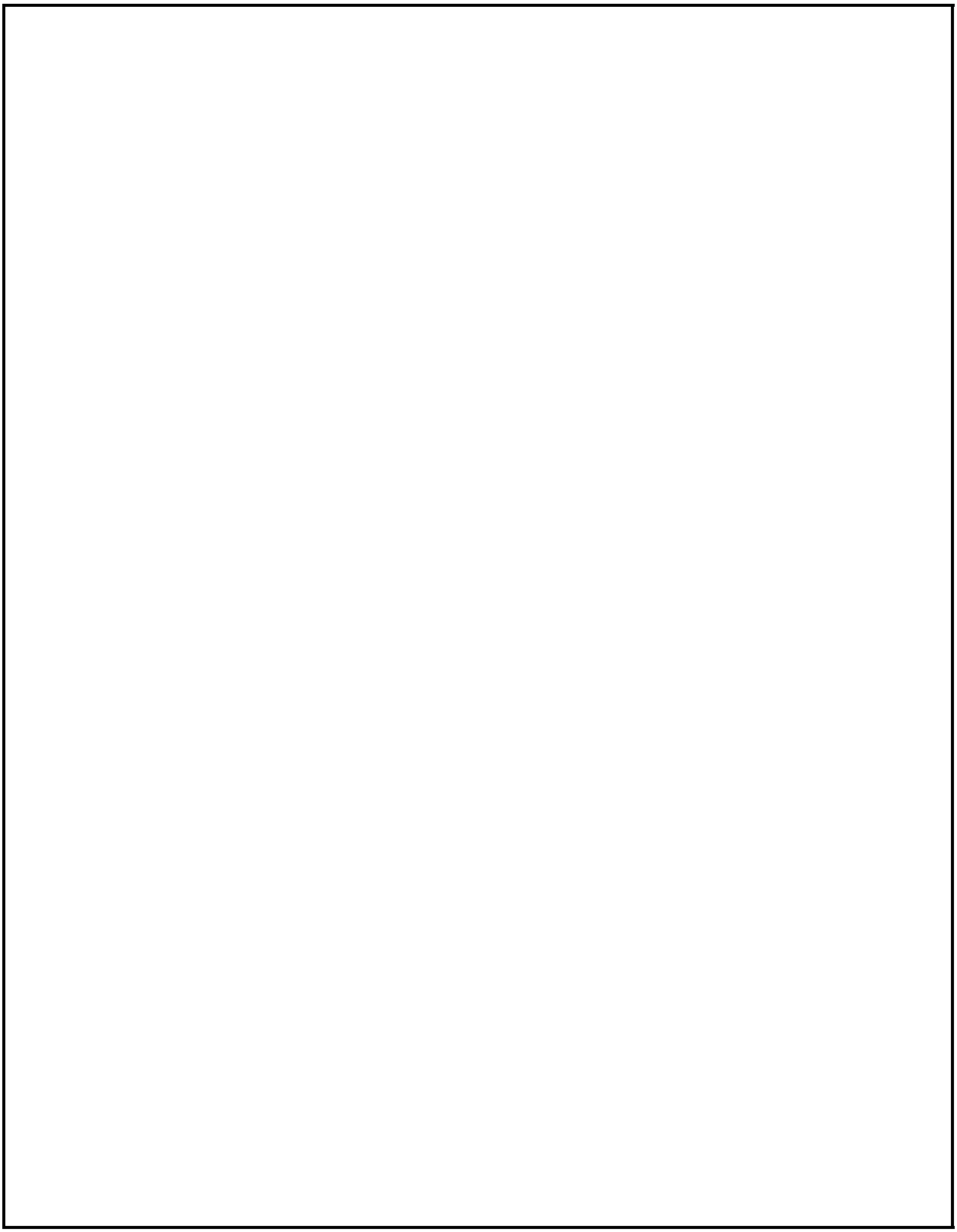
This section discusses the architecture and design of SEAtool in the REA environment. The prototype implements a proposed schema evolution methodology and assists a designer/administrator in the management and evolution of the schema. SEAtool allows the user the ability to choose evolutionary "tasks." Those tasks are then translated into a portfolio of requests and ultimately procedures that are used by the system to evolve the database. The aggregation at the task level makes the evolution of REA databases easier since users only need to know the evolution task that is required, not the specific requests or procedures necessary to complete that task. The three layer framework used in SEAtool is illustrated in figure 11.



5.1 SEAtool's Architecture

The three layer framework results in the architecture of three modules in SEAtool: SEAshell, SEAengine and SEAbase. In addition, SEAtool interfaces with the commercial package, Versant[16] Object Oriented Database Management System (OODBMS). As a prototype, SEAtool builds its own storage operations on Versant OODBMS. SEAtool's structural architecture is illustrated in figure 12.

[16] Versant is the trademark of Versant Object Technology Co.



SEAshell performs the user-interface function. A user of SEAtool recognizes the evolution task and issues the schema evolution task in the context of SEAshell. SEAshell accepts the task, interacts with the user to complete the job required by the task. In particular, SEAshell

. Provides the user interface to the user in order to determine the users evolution tasks.

. Interacts with SEAengine through evolution requests to provide the tasks that the user has specified.

SEAengine analyzes the requests issued by SEAshell and executes the schema evolution procedures to complete the requests. In particular, SEAengine

. Checks the status of the database and the context of the schema.

. Interacts with SEAShell to determine what requests are necessary to complete the user specified tasks.

. Handles the propagation effects of the evolution requests.

. Interacts with SEAbase by issuing the appropriate procedures to update the data and meta data in SEAbase.

The SEAbase module accepts the procedural call issued by SEAengine and completes the procedures using Versant functions. SEAbase is built to support an object-based model. SEAbase defines two system classes, called SEAobject and SEAclass. Those two classes are initialized, while a Versant database is created. All of the SEAbase instances are stored as instances of a system class, SEAobject. All of the SEAbase classes are stored as instances of SEAclass.

Construction of SEAtool

SEAtool, was built in a NeXTstep[17] environment to experiment with the evolution of REA databases. SEAshell and SEAengine are written in Objective C. SEAbase is defined in C++. The interface of SEAbase matches the procedure level of the schema evolution methodology. System classes such as SEAobject and SEAclass are defined by Versant C functions and encapsulated in SEAbase classes.

Evolving the Schema: Task Panels

SEAtool guides the user through the schema evolution process using "Task Guidance Panels" (TGP). For each generic task there is a TGP used to evolve the schema. A Task Guidance Panel (TGP) is a windows-based system with two components: Task Display (TD) and Task Working Space (TWS). The TD is an area used to show the schema's entities and relationships under consideration. The TWS is used to collect a user's specifications for the current task and to guide the user to complete the task. The TWS consists of an Evolution Task Catalog and a stack of Subtask Working Sheets for each task. The Evolution Task Catalog is a list of schema evolution tasks for given initial status and target pair.

The user brings the portion of the schema to be evolved into the TD within a TGP. SEAshell guides the user step-by-step through a stack of Subtask Working Sheets to complete the particular evolution task. Each Subtask Working Sheet has two parts: a Message Area and an Operation Area. The Message Area shows the system's suggestions and the user operates the evolution subtasks in the Operation Area, supplying information, as required.

[17] NeXTstep is a registered trademark of NeXT Computer Inc.

Browser Interface

SEAtool also has a windows-based browser-oriented interface. There are three main browsers: the class hierarchy browser; the class network browser; and the class inspection browser.

The class hierarchy browser allows the user to browse the class hierarchy of a forest of classes. Each hierarchal tree has its own root class. A user can focus on one branch of a subclass each time. The class network browser allows the user the ability to browse the relationship of a class and traverse to others through the whole network of the classes of a database. A user can focus on one relationship of a class each time. The class inspection browser lets the user browse the attributes defined in a class and the inherited attributes from its superclass. A user can trace the inherited attributes up to its root class. For each attribute, a user can inspect the domain class and its inverse attribute.

Summary, Contributions and Extensions

This section briefly summarizes the paper, discusses the contributions and investigates some extensions.

Summary

This paper discussed the forces behind the evolution of accounting database systems. In addition, this paper analyzed the operations necessary to change REA accounting databases to meet the requirements of evolution. Finally, this paper briefly discussed the architecture of a prototype system designed to evolve REA systems, SEAtool.

Contributions

This paper has three basic contributions. First, there has been little, if any, analysis of the forces behind the need for accounting databases to evolve. This paper provides a discussion of some of those issues and a preliminary theoretical analysis.

Second, although there have been some efforts to summarize general evolutionary operations for entity - relationship databases (e.g., Batini et al. 1992), there have been no such efforts to evolve accounting databases and tie that evolution to evolutionary forces of the firm. In addition, this paper used those forces to elicit additional operations of change and evolution.

Third, previous research on REA systems has generated at least three prototype systems. However, this paper provides the first prototype system designed to evolve REA databases.

Extensions

Although this paper investigated some of the forces behind the need for accounting databases to evolve, there is as yet no general theory. Future research could investigate a unifying theory or elicit alternative forces for the need to evolve accounting databases.

Much of the discussion here was couched in terms of relational database structures. Alternatively, an object-based approach could be used (e.g., Chen et al. 1994). This paper investigated a number of different operations that are part of the evolution process. However, there may be other approaches that can be used to evolve accounting databases. The system discussed in this paper is a prototype system designed to solve problems of evolution as a proof of concept. However, such systems typically can be improved from an efficiency and effectiveness perspective, e.g., to run faster. Such concerns are beyond the scope of this paper.

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Fuzzy Logic: Treating The Uncertainty In Expert Systems

Michelle McEacharn and Anwi Zebda

Introduction

Expert system development has been experiencing a rising growth pattern. The advent of special programming languages and "shells" has contributed to the growing popularity of expert systems, a branch of Artificial Intelligence. Advances in computer capabilities and declines in computing costs have also helped the growth. The events have made expert system technology more accessible to users. Though the technology arose from the research and development laboratories of medicine and the military, expert system development has experienced a significant involvement in the business world. The design of XCON by the Digital Equipment Corporation provided evidence of the economic benefits in improved efficiency and quality associated with an expert system [Giarratano and Riley 1989].

Within the business arena, expert system research has been substantial in the accounting and auditing context [Brown and Phillips 1990]. Many of the problems faced by accountants and auditors are ill-defined and unstructured, problems which are especially well-suited for expert system application. There has been recent expert system development in such areas as capital budgeting decisions [Brown and Phillips 1990], internal control evaluation [Bailey et al. 1985], going-concern decisions [Biggs and Selfridge 1986], bankruptcy prediction [Hsu and Wyatt 1992] and materiality judgments [Steinbart 1987]. This paper will briefly describe the expert system environment within accounting and auditing, illustrate a major criticism in the design of these systems, and introduce a potential solution to the weakness.

Background

Development and Applications

The initial growth in expert system development can be attributed to the creation of the MYCIN program, an expert system for bacterial infection diagnosis. The research culminated in the production of EMYCIN, or Empty MYCIN, a shell from which the MYCIN knowledge base had been removed. From that point, significant improvements were made in the development of expert system shells and programming languages, permitting the user to design the program to fit the specificity of the situation without the enormous program development costs [Giarratano and Riley 1989].

Messier and Hansen [1986] recognized the interest in expert systems by accountants and auditors. They described several supporting reasons for the interest, including complexity of the audit environment, ethics standards changes, and the desire for more consensus judgments. O'Leary [1987] reviewed the expert system use in accounting, describing five functional areas of accounting and illustrating the expert system work within each area. He argues that expert system development is important for accounting and auditing because of the modularity of most accounting tasks, the abundant use of rules and heuristic judgments in accounting and auditing decisions, and the value of the expert's judgment due to scarcity and cost.

To illustrate the extent of expert system research in accounting and auditing, the following tables provide information regarding some of the more prominent applications of expert system developments. The functional areas as described by O'Leary [1987] are used. Table 1 presents a sample of the expert systems used in auditing, including internal and EDP auditing.

Table 1: Auditing Expert Systems

Expert System	Developer	System Purpose
AUDITOR	Dungan [1983]	Uncollectible A/R Estimation
ICE	Kelly [1984]	Internal Control Review for Audit Planning
TICOM	Bailey, et al. [1985]	Internal Control Evaluation
INTERNAL-CONTROL ANALYZER	Gal [1985]	Internal Control Evaluation
EDP-XPERT	Hansen & Messier [1986]	Auditing Advanced Computer Environments
CFILE	Peat, Marwick, Mitchell, & Co.	Loan Loss Reserve Adequacy
AOD	Dillard & Mutchler [1986]	Going Concern Judgments
ARISC	Meservy, Bailey, & Johnson [1986]	Internal Control Evaluation
GC-X	Biggs & Selfridge [1986]	Going Concern Judgments
ICES	Grudnitski [1986]	Internal Control Evaluation
AUDITPLANNER	Steinbart [1987]	Audit Planning Materiality Judgments

Auditing has received the most attention with respect to expert system development. Initial interest appeared to be stimulated by AUDITOR, an expert system developed by Dungan [1983]. Many of the large CPA firms have either developed an expert system for specific applications or purchased commercially available programs. These firms have protected much of the information related to their systems due to competitive pressures. This protectionism signifies the increased importance of expert systems in auditing.

Many of the problems encountered in auditing have ideal characteristics for expert system application. Messier and Hansen [1986] indicate that auditing problems tend to be semi-structured or highly unstructured, where there are ill-defined concepts and multiple potential solutions. Since the quality of the judgment is a function of the expert and the expert system is designed to emulate the expert's judgment, they contend further that an expert system is appropriate for such problems [Messier and Hansen 1986].

Some of the more unstructured problem areas in auditing involve materiality decisions, control evaluations, audit opinions, and going concern judgments. As indicated by Table 1, internal control evaluation appears to have received substantial attention. Systems related to assisting with going concern decisions have received some attention as well. Surprisingly, the expert system research involving materiality judgments, a highly unstructured problem judgment area in which expertise provides the optimal solution, has not been as intense. Materiality is not a nominal variable and often is judged differently by various auditors [Moriarity and Barron 1976], thus contributing toward its unstructured nature.

Applications of expert system technology in the management accounting context are illustrated in Table 2. Corporations involved in expert system development include such notables as IBM, Digital Equipment Company, and Texas Instruments. The development takes place in other more non-technical corporations such as Associated Grocers. Systems have been developed to assist in capital investment decisions, transfer pricing determinations, and performance evaluation.

Table 2: Managerial Expert Systems

Expert System	Developer	System Purpose
FAME	IBM	Customer Need Analysis
Capital Investment System	Texas Instruments	Departmental Capital Investment Decisions
Associated Grocers' Workbench	Associated Grocers	Buying, Pricing, & Promotion Planning
Arthur D. Little's Expert System	Arthur D. Little	Variance Analysis
XCON	Digital Equipment Company	VAX System Configuration
BUCKS	Digital Equipment Company	Division Performance Evaluation
ICOR	EXXON	Transfer Pricing and Tax Adjustments

Table 3 presents expert system work performed in the area of taxation. TAXADVISOR and ExperTax are perhaps the two most recognized systems. Note that virtually all of the systems are characterized with a planning focus. The accounting information systems and financial accounting areas have recently received attention (e.g., McDuffie et al. 1992, Hsu and Wyatt 1992). However, this is a relatively undeveloped niche and, with continued improvement in expert system technology, should be fertile ground for the additional application.

Table 3: Taxation Expert Systems

Expert System	Developer	System Purpose
TAXMAN	McCarthy	Reorganization Tax Planning
TAXADVISOR	Michaelsen	Financial Estate Planning
ExPerTax	Coolers & Lybrand	Tax Accrual and Planning

Though not included as a functional area of accounting, education is a significant factor in the accounting discipline. A major consequence that results from the design and development of an expert system is a more thorough understanding of the decision-making process for that particular problem. Additionally, most systems have explanation facilities which enable the users of the expert system to query the system for explanation of the process, thereby representing an excellent preparation and training mechanism. These attributes cause the expert system to be a potentially significant resource in accounting education. Some of the recent accounting education expert system research includes Scott, McEacharn, and Boyd [1992] and Goldwater and Fogarty [1992].

Advantages and Disadvantages

Giarratano and Riley [1989] list many direct benefits of expert system development. These benefits include increased availability and reliability of expert judgment, reduced cost, fast and unemotional response, and its use as an intelligent tutor. The knowledge gained from the intense study of the expert's decision process during development of the system is described as an indirect benefit. Lehman, Malley, and Cassidy [1991] agree and also argue that the expert system will never replace the expert's opinion but will be a valuable aid in confirming the expert's judgment. Benefits more directly associated with accounting and auditing include improved efficiency in time, reduced litigation costs, and greater consensus of opinion. With appropriate development techniques, maintenance of the expert system is relatively minimal and the expert system can be easily adapted for environmental changes which necessitate adjustment.

There are disadvantages associated with expert system technology. The tremendous costs to develop the system has been a barrier in the past but, as indicated earlier, language and expert system shell advances have alleviated this problem substantially. Another commonly mentioned weakness of an expert system is its domain specificity. The expert system is not currently able to apply the rules from one problem domain to another. O'Leary [1987] describes

limitations specifically related to the accounting arena, specifically that changes are continually necessary to the knowledge base and that the expert system only represents an aid, not a replacement, for the expert's judgment.

Two major limitations of important concern to expert system developers are the knowledge acquisition bottleneck and the treatment of uncertainty. There has been significant research related to both of these problems. The knowledge acquisition bottleneck relates to the acquisition of the knowledge from the expert for programming into the expert system. Lesmo, Saitta, and Torasso [1985] contend the disparity between the rigorous programming requirements and an expert's normal knowledge expression is a primary influence on the knowledge acquisition bottleneck. Messier and Hansen [1988] agree that fuzzy and ill-defined concepts contribute to this problem. This is because most experts find it extremely difficult, and often impossible, to explicitly detail their decision thought process. Complicating the task further, the expert may be able to detail the logic process used in the problem but may be unable to explain the process in sufficient precision to permit coding. Often the expert uses "fuzzy" or ill-defined language, terms such as "significant" and "strong", to explain the process and its variables.

Another very important consideration in expert system development is the treatment of uncertainty. Mamdani and Efstathiou [1985] indicate three problems which must be overcome before expert system development becomes fully feasible. These include knowledge representation, inference procedures, and knowledge-base management. Fundamental to all of these problems is the treatment of uncertainty. New approaches to handling uncertainty have been explored but, in accounting expert systems, probabilistic logic has been the typical solution method.

Probabilistic Logic in Accounting Expert Systems

The most commonly used method for handling uncertainty in accounting and auditing systems is probabilistic logic [Zimmerman 1987; Mamdani and Efstathiou 1985]. An examination of the IF-THEN rules in Hansen and Messier's [1986] expert system, EDP-XPERT, illustrates the probabilistic nature of the rules. The logic is based on probability theory and represents a way of quantitatively dealing with uncertainty. Probability theory was based on games of chance, e.g. rolls of the dice and draws from a deck of cards. Such events can be reproduced indefinitely. Additionally, the possible states of nature are bounded and precise, as is the total possible states of nature. For example, probabilistic logic can be used to give the odds of drawing a queen from a deck of 52 cards--there are four queens, each with a one in 52 chance of being drawn. That results in a four in 52 chance of drawing a queen from the deck. The likelihood of drawing an ace from the deck is also four in 52.

There are two key issues to notice. First, the desired outcome is well-defined (e.g., draw one of four queens) and the total possible states of nature are bounded (e.g., faces of all 52 cards are known and explicit in terms of their definition). The key second consideration here, however, is that the card to be drawn, assuming a fair game, is completely random. The drawn card could be any one of the total deck. There is no confusion as to the face of the card once it has been drawn and each card has the same likelihood of being drawn as any other. Thus, the form of uncertainty quantified by probabilistic logic is randomness.

Randomness is certainly an important consideration in many problem domains. Many types of uncertainty in accounting and auditing, however, do not appear to have strong characteristics of randomness. Randomness is a significant part of accounting and auditing in some respects, such as in statistical sampling for compliance and quality control sampling. On the other hand, determining whether a particular internal control weakness is material enough to warrant extensive substantive testing is not a matter of randomness. Luck of the draw does not determine material weaknesses. Rather, the materiality of the weakness is determined by such things as financial outlook, firm size and position, employee relations, and other discovered weaknesses. These influences are often described by auditors in imprecise and vague language. For example, "good" financial outlook, "large" firm, "weak" financial position, and "low" morale are all measurements which could be made by the auditor in determining materiality for which there is not a quantitatively defined measurement of what "good" or the other such vague concepts mean. All of these facts, subtleties, and relationships are assimilated in the mind of an auditor and used to determine materiality.

Jackson [1990] argues that vagueness is the influencing factor in the uncertainty associated with many problem areas. Further illustrating this point, Bonissone and Tong [1985] describe four causes of uncertainty of which all primarily deal with the inaccuracy, imprecision, incompleteness, and ambiguous (conflicting or changing definitional meanings of

terms) nature of information. The uncertainty associated with accounting and auditing appears to be a primary consequence of the vagueness and ambiguity which exists in the discipline [Zebda 1991]. Gangolly [1988] agrees that the "syntactic ambiguities in accounting" presents problems and that ambiguities may be either intentional or unintentional. This type of uncertainty is evident in many areas of accounting and auditing, including going concern judgments, internal control evaluation, performance evaluation, fairness of financial reports, and disclosure compliance.

In each of these areas, as well as in other areas of accounting and auditing, the randomness associated with these events is not the criteria on which judgments are made. It may be true that one in every ten companies will file for bankruptcy within the next year but the auditor cannot merely assume a 10% probability in making a going concern judgment related to a specific company. The auditor must assimilate company specific information, often ill-defined and incomplete, to determine the likelihood. Probabilistic logic, designed to measure uncertainty related to randomness, is not appropriate in these types of situations.

Yet, probabilistic logic is most commonly used in the development of accounting expert systems. Dungan [1983], Hansen and Messier [1986], and Michaelsen [1984] attempt to handle the uncertainty resulting from the ambiguity and vagueness problem through the use of uncertainty factors in their development of accounting expert systems. However, Jackson [1990] illustrates several distinct weaknesses of certainty factors and argues that they may merely represent an offspring of the traditional probabilistic approach. McKee [1986] contends that the divergence in accounting theory and practice is a result of the reluctance on the part of accountants to incorporate uncertainty into their decision models. He further argues that this uncertainty cannot be assumed away. Ambiguity and vagueness characterize the uncertainty of many key aspects of accounting and auditing information. To better emulate an expert's decision making process and integrate the uncertainty which is characterized in accounting and auditing, a different logic may be more appropriate in the design of the accounting and auditing expert system.

An Alternative

Fuzzy logic could represent the most appropriate method for dealing with the uncertainties involved in many accounting and auditing applications. Zimmerman [1987] argues that differing types of uncertainties require the use of varying types of tools, of which "fuzzy set theory is especially suited". Mamdani and Efstathiou [1985] agree that probabilistic approaches are not comprehensive enough for all problems and argue that fuzzy logic can provide significant help in the treatment of uncertainty. Fuzzy logic has been recognized by other researchers as a viable alternative to probabilistic theory (e.g., Whalen et al. 1987; Giarratano and Riley 1989). The logic has been used in many fields of application, particularly of a technical nature. For instance, fuzzy logic has been used in the design of camcorders, microwave ovens, subway trains, and elevators.

Recently, emphasis has been placed on the use of the logic in the design of expert systems. As the interest in fuzzy logic has increased, several fuzzy programming tools have been developed, including PRUF, FUZZY, FRIL, and REVEAL. Systems using fuzzy logic have been developed in the areas of medical diagnosis (CADIAC) and damage assessment (SPERIL-II) [Zimmerman 1987]. Fuzzy logic has also been used in a relatively few business and/or accounting system applications. These applications include such systems as: PRICE [Whalen and Schott 1983], a management simulation game aid; fINDex [Schott and Whalen 1983], a sales forecasting expert system; FAULT [Whalen, Schott, and Ganoe 1982], a financial ratio analysis mechanism; FANFARE(S), an expert system extension of FAULT; and STRATASSIST [Green 1984], a strategic planning expert system [Whalen et al. 1987]. Thus, the extensive use of fuzzy logic validates its possibility as a significant tool for an accounting or auditing expert system. This paper serves to encourage the use of fuzzy logic in accounting and auditing, arguing for its continued application to the discipline.

An Introduction to Fuzzy Logic

It is the intention here to provide a brief introduction to fuzzy logic. For more detailed descriptions, the interested reader can refer to Zadeh [1965], Zadeh [1989], or Zebda [1991]. Using fuzzy logic in an expert system, the knowledge base is developed through the use of fuzzy production rules. Characterizing the use of fuzzy rules is the use of linguistic variables, or words which are close to normal descriptive phrases (e.g., fast, low, some, most). This ability to use

linguistic variables enhances the knowledge acquisition process [Whalen et al. 1987]. Jackson [1990] also indicates that a popular aspect of fuzzy logic is its relatively natural language representation capabilities.

The fuzzy reasoning used in expert systems originated with fuzzy set theory and the work of Zadeh [1965]. In ordinary set theory, elements of a set are either a member of a set or they are not a member of a set. These sets are often called "crisp" sets because the inclusion of an element as a member of the set is precise, or "crisp", represented by a "0" for non-member and a "1" for a member. There is an all-or-nothing relationship between the element and the set. Fuzzy set theory represents a generalization of ordinary set theory. Elements of a set are permitted to be less than complete elements of a set, within the range of "0" to "1". For instance, an item may be an element of a set with a degree of association of .7, meaning that the item is a fairly strong member of the set but is not a complete member of the set.

A fuzzy set can be formally defined by $A = \{u_A(x)/x\}$, where A is a fuzzy set of a universe E. Each element x in the universe E is associated with the fuzzy set A with a compatibility of $u_A(x)$. This compatibility of the element x with the fuzzy set A is referred to as the membership or compatibility function. The compatibility of an element with a set in ordinary set theory is binary, represented by either $u_A(x)=1$ if the element is a member of the set, or $u_A(x)=0$ if the element is not a member of the set. In fuzzy set theory, gradual membership of an element with a set is permitted by allowing $u_A(x)$ to take on any value within the closed interval 0 to 1, such as $u_A(x)=.2$, $u_A(x)=.4$, or $u_A(x)=.9$.

A basic illustration using fuzzy set theory will help solidify the mathematics involved. Using an accounting example, assume that an auditor is evaluating the materiality of discrepancies found in a specific accounting function. To keep the mathematics straightforward, the set of possible discrepancies will be assumed to be finite and discrete. Suppose the set of possible dollar discrepancies which may appear in an account may be represented by the universe E = {$0, $10, $20, $30, $40, $50, $60}. The occurrence of $0 discrepancies in the account would indicate, with the utmost confidence, that the level of discrepancy is immaterial to the auditor. On the other hand, the occurrence of a $60 discrepancy in the account would surely signify a material discrepancy. The vagueness associated with the problem occurs in the values between $0 and $60. Is a $50 discrepancy material? Is a $40 discrepancy material? At what point exactly does the discrepancy move from the material set to the immaterial set? Fuzzy set theory specifically addresses this problem by permitting the gradual inclusion of items to a particular set. Table 4 illustrates how, using fuzzy set theory, the dollar amount of the account discrepancy may be related to subjective materiality values used by the auditor.

Table 4: Discrepancy/Materiality Association

	Dollar Amount of Discrepancy						
Level of Materiality	$0	$10	$20	$30	$40	$50	$60
Immaterial	1.0	.9	.7	.5	.3	.1	.0
Questionable	.0	.3	.6	1.0	.6	.3	.0
Material	.0	.1	.3	.5	.7	.9	1.0

Table 4 indicates the degree to which each of the possible account discrepancy amounts may be related to each Level-of-Materiality set. As indicated by the discussion related to ordinary set theory, the occurrence of $0 discrepancy in the account would be a complete member of the Immaterial set, represented by the degree of membership of 1.0. At the other extreme, the occurrence of a $60 discrepancy definitely indicates materiality to the auditor, represented by the 1.0 degree of membership of $60 to the Material set.

Notice, however, that as the dollar amount of discrepancy decreases, the degree to which the amount is associated with the Material set decreases. A discrepancy of $50 is a fairly strong member of the set, represented by .9, whereas a $40 discrepancy is still a rather significant member, with a degree of membership of .7, but not as strong a member as the $50 discrepancy. The occurrence of a $0 discrepancy has absolutely no relationship to the Material set, evidenced by the degree of association of .0. On the other hand, as the dollar amount of discrepancy decreases, the strength of the relationship of the discrepancy to the Immaterial set increases.

The ambiguity which results from attempting to define the exact level at which an item moves from that of materiality to immateriality is effectively considered by fuzzy set theory. The theory permits a decision state to be something other than binary, meaning a set can exist to identify those items which are neither material nor immaterial but which are

questionable. According to the data provided in Table 4, an occurrence of a $30 discrepancy is a complete member of the Questionable set, represented by 1.0, and is somewhat a member of both the Immaterial and the Material sets, represented by .5 in both cases. As the dollar amount of the discrepancy either increases or decreases, the association with the Questionable set declines. The dollar amount tends to become more fully associated with one of the other sets.

Using fuzzy set notation to present the same concepts presented in the previous example, the set "Questionable Materiality" can be represented by the fuzzy set A, subjectively defined as:
$u_A(0) = 0$;
$u_A(10) = 0.3$; $u_A(20) = .6$; $u_A(30) = 1.0$; $u_A(40) = 0.6$; $u_A(50) = 0.3$;
$u_A(60) = 0$.

The set A can then be written as:

A = {(0/0), (.3/10), (.6/20), (1.0/30), (.6/40), (.3/50), (0/60)}.

This expression for set A can be simplified to include only those elements which possess at least some compatibility with the set A, as presented by the following:

A = {(.3/10), (.6/20), (1.0/30), (.6/40), (.3/50)}.

As indicated above, this example illustrates that an occurrence of a discrepancy of $30 in an account indicates Questionable Materiality of the item, represented by the full membership (1.0) in set A. The occurrence of a $50 discrepancy is a member of the Questionable Materiality set to some extent (.3), but does not exhibit a strong compatibility to set A. The occurrence of a $50 account error would probably be much more strongly associated with a set (B) identified as "Material Discrepancy".

Basic mathematical operations are different in fuzzy set mathematics as compared to ordinary set theory. The following example illustrates the use of fuzzy set mathematics in three basic set operations. These operations are the intersection, the union, and the complementation and are represented by the operators "and", "or", and "not", respectively.

The universe is represented by set E. Fuzzy sets A and B are subsets of E and are described by the membership functions $u_A(x)$ and $u_B(x)$, respectively. The following membership functions describe the mathematical operations of intersection ($A \cap B$), union ($A \cup B$), and complementation (A'), respectively.

$$u_{A \cap B}(x) = u_A(x) \wedge u_B(x), \quad (1)$$
$$u_{A \cup B}(x) = u_A(x) \vee u_B(x), \quad (2)$$
$$u_{A'}(x) = 1 - u_A(x) \quad (3)$$

The operation of taking the minimum is represented by $\wedge$, whereas the operation of taking the maximum is indicated by $\vee$.

Using Zebda's [1991] illustration, let $E = \{x_1, x_2, x_3, x_4\}$ represent the set of possible sampling procedures. Two fuzzy subsets of E may be defined to be set A (set of efficient procedures) and set B (set of inexpensive procedures), represented by the following:

$A = \{(.2/x_1), (0/x_2), (.8/x_3), (1/x_4)\}$,
$B = \{(.8/x_1), (.5/x_2), (.1/x_3), (0/x_4)\}$.

Sets A and B can be used to identify the efficiency and costs associated with the set of sampling procedures. For example, procedure x_4 is an efficient procedure, indicated by its compatibility of 1 to set A, but is an expensive procedure, indicated by its compatibility of 0 to set B.

The example may be extended to illustrate the intersection, union, and complementation of these sets. The equations (1) - (3) are used to describe $A \cap B$ (the set of efficient and inexpensive procedures); $A \cup B$ (the set of efficient or inexpensive procedures); and, A' (the set of inefficient procedures). These sets are indicated by the following:

$(A \cap B) = \{(.2/x_1), (0/x_2), (.1/x_3), (0/x_4)\}$,
$(A \cup B) = \{(.8/x_1), (.5/x_2), (.8/x_3), (1/x_4)\}$,
$A' = \{(.8/x_1), (1/x_2), (.2/x_3), (0/x_4)\}$.

As can be seen by the previous set descriptions, the intersection of set A and set B is derived by taking the minimum level of compatibility of a specific element to both sets. For example, procedure x_1 has a compatibility of .2 to the set of inefficient procedures (set A) and a compatibility of .8 to the set of inexpensive procedures (set B). The procedure x_1 has a compatibility of .2, the minimum compatibility to each of the two individual sets, to the set of both efficient and inexpensive procedures (the intersection of set A and B). On the other hand, the union of sets A and B is derived by taking the maximum level of each element's compatibility to the individual sets. The procedure x_1 has a compatibility of .2 to set A and a compatibility of .8 to set B.

Consequently, the maximum (.8) then represents the association of the x_1 procedure to the set of either efficient or inexpensive procedures. To derive the set A', the degree of membership of each element is merely subtracted from 1 to arrive at the compatibility of the element to the set A'. Some ordinary set properties, such as commutativity and associativity, hold in fuzzy set theory. Other properties do not hold for fuzzy sets. For example, in fuzzy set mathematics, the negation is not complementary. Further discussion regarding the axioms of fuzzy set theory may be found in Bellman and Giertz [1973], Fung and Fu [1975], and Gaines [1976].

Conclusion

Fuzzy logic is based on the premises of fuzzy set theory. Thus, this logic permits the use of imprecise or vague concepts in both the development of the expert system as well as in the implementation of the system. An examination of Steinbart's [1987] expert system, AUDITPLANNER, can be used to illustrate the ambiguous nature that is being addressed by the probabilistic approach. Included as part of the knowledge base rules are terms such as "too high", "too low", and "very likely". Fuzzy logic, which specifically addresses the type of uncertainty related to ambiguity and vagueness, would be a more appropriate method.

Whalen et al. [1987] contends that "the flexibility to handle knowledge at various levels of specificity or vagueness and in a natural and expressive vocabulary" and the "flexibility in the way data are input" are important benefits of fuzzy logic in expert system design. Lesmo, Saitta, and Torasso [1985] also contend that the greatest contributions of fuzzy logic is its mathematical ability to handle vagueness and the ability to use natural linguistic variables. The two major limitations of expert system development are addressed by these benefits. The use of linguistic variables facilitates the knowledge acquisition process, improves the capability of the system to deal with vague and ambiguous concepts, and increases the expert system's applicability to a wide range of problems. The uncertainty associated with accounting and auditing tends to be primarily a result of the vagueness and ambiguity which is an inherent part of accounting and auditing. Fuzzy logic represents a potentially attractive method of dealing with this uncertainty. The benefits obtained from the use of fuzzy logic in such systems include reductions in knowledge acquisition costs, a means of reconciling varying expert judgments, and a mechanism which more realistically emulates the decision making process of the expert.

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Bankruptcy Prediction Via A Recursive Partitioning Model

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ABSTRACT

Prior research described a bankruptcy prediction model, by the author, employing two financial ratios that achieved 97% accuracy. That model had been derived via the recursive partitioning algorithm ID3 from financial data for 60 public companies. The algorithm formed a variety of decision trees which were pruned using judgmentally based pruning rules and a previously published continuity theory to form the final model. Sample size and the judgmental pruning rules were limitations of this prior research .

This research extended the prior study by testing the model on a different sample of 202 public companies. This testing indicates that the original model was 86% accurate in classifying companies that were not going bankrupt but only 54% accurate in classifying bankrupt companies [overall accuracy of 70%]. The research question then became, "Was the change in model performance due to the variables employed or to the classification points selected for the variables?"

To answer the previous question, the recursive partitioning algorithm ID3 was used to recalculate optimum classification points for the 202 company sample. This resulted in a second model using the same two ratios as the original model but employing a different classification rule and points. This model was 92% , 82%, and 79% accurate in predicting bankruptcy one, two and three years prior for the 202 company sample. This model was also 87% accurate on the original sample of 60 companies.

This research indicates that ID3 has been used to develop a robust bankruptcy prediction model that is simple and consistent with the temporal continuity theory. The results of this research should be of interest to individuals interested in bankruptcy prediction or application of recursive partitioning algorithms

Introduction

McKee [1995-A] utilized the recursive partitioning algorithm ID3 to analyze financial data for 60 public companies in order to predict bankruptcy. ID3 is a machine learning technique which forms binary partitions based on attribute values in order to classify mixed cases into their associated classes. ID3 was employed on the 60 cases to form variety of decision trees. The decision trees were judgmentally pruned using a previously published continuity theory to form a final model. A theoretically consistent model that was 97% accurate in predicting bankruptcy for the 60 companies was developed. Limitations of the prior research were the sample size and the judgmental pruning rules.

The objective of this research was to test and validate the previously developed model for bankruptcy prediction. As previously reported [McKee, 1995-B], this research extended the prior study by testing the model on a different sample of 202 public companies [see Table 1 for companies utilized in the current study]. This testing indicated that the original model was 86% accurate in classifying companies that were not going bankrupt but only 54% accurate in classifying non-bankrupt companies [overall accuracy of 70%]. The research question then became, "Was the change in model performance due to the two variables employed or to the classification points selected for the variables?"

To answer the previous question, the recursive partitioning algorithm ID3 was used to recalculate optimum classification points for the 202 company sample. This resulted in a second model using the same two ratios as the original model but employing different classification points. As illustrated in Table 2-Predictive Accuracy of New Model on 202 Company Sample this model was 92% , 82%, and 79% accurate in predicting bankruptcy one, two and three years prior for the 202 company sample. Table 3-Companies Utilized In Prior Study lists the companies used in the prior studies and the predictions of the new model. As shown in Table 4-Predictive Accuracy of New

Model On 60 Company Sample his model was also 87% accurate on the original sample of 60 companies. This research indicates that ID3 can be used to develop a robust bankruptcy prediction model that is simple and consistent with the temporal continuity theory. The results of this research should be of interest to individuals interested in bankruptcy prediction or application of recursive partitioning algorithms.

Recursive Partitioning Algorithms

Inductive learning is the process of generating explanations for case outcomes from data in a set of cases . It may be characterized as "learning by example." One type of inductive learning is recursive partitioning. This describes a general class of techniques which split sample data into subsets according to some criterion in order to develop knowledge structures from the sample.

Recursive partitioning was developed as a nonparametric technique based on theoretical analysis by Friedman [1977] and Gordon and Olshen [1978]. It performs classification by partitioning the independent variables into subgroups. No a priori distributional assumptions are imposed on the variables. The search algorithm starts by selecting the independent variable the minimizes the expected misclassification costs. It establishes an optimal cutoff value for this variable and partitions the overall set of cases into two groups based on this cutoff value. It then analyzes the subgroup with the greatest number of misclassifications and determines if that group can be further partitioned using one of the independent variables. It then proceeds to partition that subgroup through the previous process. The partitioning process continues until no further partitioning is feasible. This process results in a decision tree where every node is divided into two branches and the branches lead to a classification decision. Recursive partitioning, as originally developed, considers both prior probability and costs of misclassifications in determining the best decision rule. It also determines decision rules based on measures of sample impurity. A variation on the recursive partitioning algorithm is "ID3." It uses a measure of entropy to form decision rules. If prior probabilities are determined from the original sample proportions and the costs of misclassifications are assumed to be equal, then ID3 produces a knowledge structure similar to recursive partitioning. ID3 is, therefore, a category of recursive partitioning.

ID3 is a machine learning technique developed by Quinlan(1979,1982) which he called "interactive dichotomizer 3 (ID3)." This method takes a set of cases for which both selected attribute values and outcomes are known, and produces a decision tree that correctly classifies these cases based on their attribute values. ID3 uses the information-theoretic measure of entropy to assess the information value of each attribute and develop splitting points based on this value. "ID3 has been used successfully for various classification and prediction problems." (Chen et. al., 23)

The ID3 measure for misclassification is the entropy (measure of disorder), designated E (C) which is calculated for a sample according to the following formula:

$$E(C) = -\sum_{i=1}^{n} p(c_i) \log_2 p(c_i)$$

$i = 1,...,n$ Index of possible classifications; in this case n = 2, where i = 1, bankrupt, i = 2 not bankrupt

c = classification group

$p(c_i)$ = Probability of occurrence for class i

[Messier and Hansen, 1988, p. 1408]

When a data set is split around a splitting point, the data on each side of the splitting point forms a sub-table. The entropy of each sub-table E (C|aj) is given by:

$$E(C|A) = -\sum_{i=1}^{n} p(c_i|a_j) \log_2 p(c_i|a_j)$$

where n is the number of subsets of c_i .

The entropy for the entire table after a split around an attribute is then calculated according to the following formula:

$$E(C|A) = \sum_{j=1}^{M} p(a_j)\, E(A|a_j),$$

where M is the number of subsets

[Messier and Hansen, 1988, p. 1408]

A detailed explanation and example of how ID3 works is provided in McKee's [1995-A] paper describing the prior study.

Summary Of Prior Research

The prior research [McKee, 1995-A] used the ID3 inductive inferencing algorithm to extract knowledge structures from data on 60 actual companies. Once the knowledge structures were extracted, a previously published theory with related model was used select the data utilized and to evaluate pruning choices among the various knowledge structures.

Guiding Theoretical Model

McKee [1986] proposed a temporal continuity theory to replace the classical going-concern concept. This theory suggested variables that might be appropriate for predicting going-concern status. It also provided a basis for evaluating the knowledge structures developed.

The temporal continuity theory posits that a firm has a planning or operating horizon related to resource commitments made by the firm. A firm possessing continuity must have " . . . expectations of both sufficient current resources to fulfill its commitments and sufficient market returns or benefits flowing to it [McKee, 1986, p. 27]."

"Current resources" refers to either the actual liquid assets available or that may be made available (i.e., a line of credit) to an entity. It may be estimated using a variety of current liquidity surrogates. For example, the current ratio is a common current liquidity surrogate.

"Sufficient market returns" refers to the prospect of future cash flows to the entity. These cash flows may be generated from earning capacity or borrowing capacity based on future earning potential. Surrogates for estimating future cash flows are projected earnings or projected cash flows.

Integration With Theoretical Model

The knowledge structure developed in the original research was consistent with the temporal continuity theory model. The two ratios identified through that research, the Current Ratio and the Net Income / Total Assets ratio are surrogates for the "current resources" and "positive long-run resource flows" in the temporal continuity theory. Also, the final knowledge structure included these ratios in an order that was consistent with the temporal continuity theory. Thus, prior research indicated that the final optimal cognitive system was an empirically successful implementation of the temporal continuity model in the form:

IF the scaled Current Ratio is less than 24 and
IF the scaled Net Income / Total Assets ratio less than 81
THEN the firm will go bankrupt.
ELSE the firm will not go bankrupt.

In summary, the final knowledge structure developed in the prior research was 97% accurate in classifying all sixty companies and was consistent with the previously posited continuity theory.

The Current Research

The companies utilized in the prior and current studies were selected from Compact Disclosure which reports financial data for all public companies filing with the U.S. Securities and Exchange Commission. The fiscal years utilized spanned the four year period 1986 to 1989. One-half of these companies were going-concerns and one-half were non-going-concerns.

Going-concerns were defined as companies having a positive cash flow from operations for the most recent five year period. Non-going concerns were defined as companies that have either filed for bankruptcy or had a significant subsidiary file for bankruptcy.

A minimum existence period of five years was adopted for companies utilized to eliminate startup companies from consideration. Table 1-lists the companies included in this study along with related data about fiscal periods, company assets, standard industrial classification number, current ratio, net income/total assets ratio, and model prediction for the company..

Results

The original model's classification accuracy was tested on the sample of 202 public companies. One-half of the 202 companies actually went bankrupt subsequent to the period for which data was evaluated while the other half continued as healthy, non-bankrupt companies.

The current ratio for these companies is displayed in sorted order in Figure 1-Current Ratio of 202 Bankrupt and Non-Bankrupt Companies. The bankrupt companies in Figure 1 have a separate symbol representing them so they may be distinguished from the bankrupt companies. As illustrated in Figure 1 and consistent with the continuity theory, the bankrupt companies have a lower current ratio than the non-bankrupt companies.

The net income/total assets ratio for these companies is displayed in sorted order in Figure 2- Net Income/Total Assets Ratio of 202 Bankrupt and Non-Bankrupt Companies. Consistent with Figure 1, the symbol representing the bankrupt companies is different from the symbol for the non-bankrupt companies. Consistent with temporal continuity theory the bankrupt companies have a lower net income/total asset ratio than the non-bankrupt companies. The degree of separation for the two sub-samples is greater than in Figure 1.

This study found that the original model was 86% accurate in classifying the 101 companies that did not go bankrupt but only 54% accurate in classifying 101 bankrupt companies. Therefore, the original model 's overall accuracy on the sample of 202 companies was 70%. Given the significantly lower predictive accuracy level for the current sample as compared to the development sample the focus of the research then shifted to trying to explain why the lower accuracy level occurred. The research question then became, "Was the poor performance of the model due to the two ratios employed or to the classification points selected for the variables?"

To answer the previous questions, the inductive inferencing algorithm ID3 was then used to recalculate optimum classification points for the 202 company sample. The sample data were analyzed using EXPERT-EASE, an inductive inferencing software system employing ID3 [Human Edge Software, 1983]. This resulted in a new

model using the same two ratios as the original model but employing a different classification rule and points. As shown in Table 2, this model was 92% , 82%, and 79% accurate in predicting bankruptcy one, two and three years prior for the 202 company sample.

The new model can be expressed as a decision rule in the following form:

```
IF      the Current Ratio is less than .64  or
        IF      the Net Income / Total Assets ratio is less than 0
                THEN    the firm will  go bankrupt
                ELSE    the firm will not go bankrupt
```

This new model utilizes actual ratio values rather than the scaled ratio values used in the previous study. This means that this model should be more easily understood and used by various parties since no data scaling is needed to use the model.

Table 3 lists the companies included in the prior study along with their SIC number, current ratio, net income/total asset ratio, and classification prediction from the revised model. As shown in Table 4, the revised model was 87% accurate in classifying the original 60 company sample used in the previous research. This accuracy level provides validation of the for the revised model.

The results achieved with the new model indicated that the problem with the prior model was the classification rule and points selected rather than ratios utilized. This finding provides additional support for the theoretical model underpinning the prior empirical model.

Limitations of this research include:
The pruning process employed in the prior study, although supported by theory, was somewhat subjective,
Development of cutting points from the entire current 202 company sample rather than a sub-sample of this and the prior studies samples which would permit use of the remaining samples for validation of the model,
Use of equal prior probabilities of occurrence which does not reflect the actual occurrence rate for bankruptcy,
Failure to incorporate relative costs of different types of misclassifications since these might be expected to be significantly different..

Discussion And Conclusions

Business failure imposes significant costs on stakeholders. These stakeholders frequently seek to recover some of these costs from parties that they believe should have alerted them to the potential business failure. One such party that has been frequently held to be accountable is the external auditor. U.S. auditing standards require the auditor to comment in the audit report when “substantial doubt” about the going concern status of a company exists.

“Auditors have used a variety of decision aids including complex statistical models to assist them in making going concern judgments. Research indicates that experienced auditors can only correctly forecast bankruptcy about 83% of the time. It also indicates that auditors only disclose possible bankruptcy for about 45% of the companies that actually go bankrupt within one year after receiving the auditors' report. Furthermore, very recent research indicates that 62% of the companies receiving a going concern modification in their auditors' report did not go bankrupt in the year after receiving that report. Clearly, auditors have a difficult time forecasting and disclosing bankruptcy.” (McKee, 1995-A, p.35)

The model developed in the current research used only two publicly available ratios and was 92% , 82%, and 79% accurate in predicting bankruptcy one, two and three years prior for the 202 company sample. It was 87% accurate in predicting bankruptcy one year prior for the companies used in the prior research study.

The results of this research should be of interest to individuals interested in bankruptcy prediction or application of inductive inferencing algorithms. This would include auditors, investors, creditors, and other stakeholders interested in making highly accurate bankruptcy predictions.

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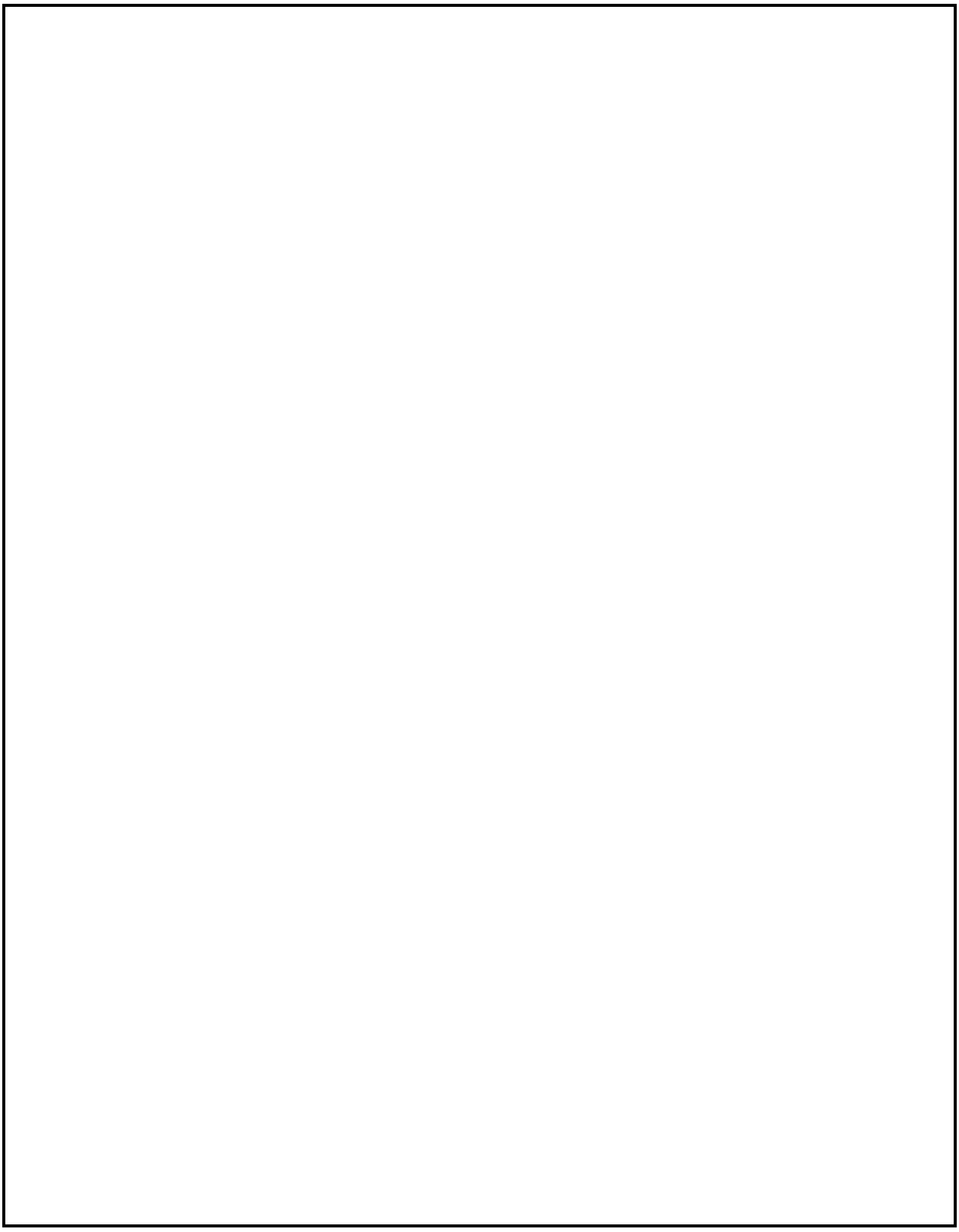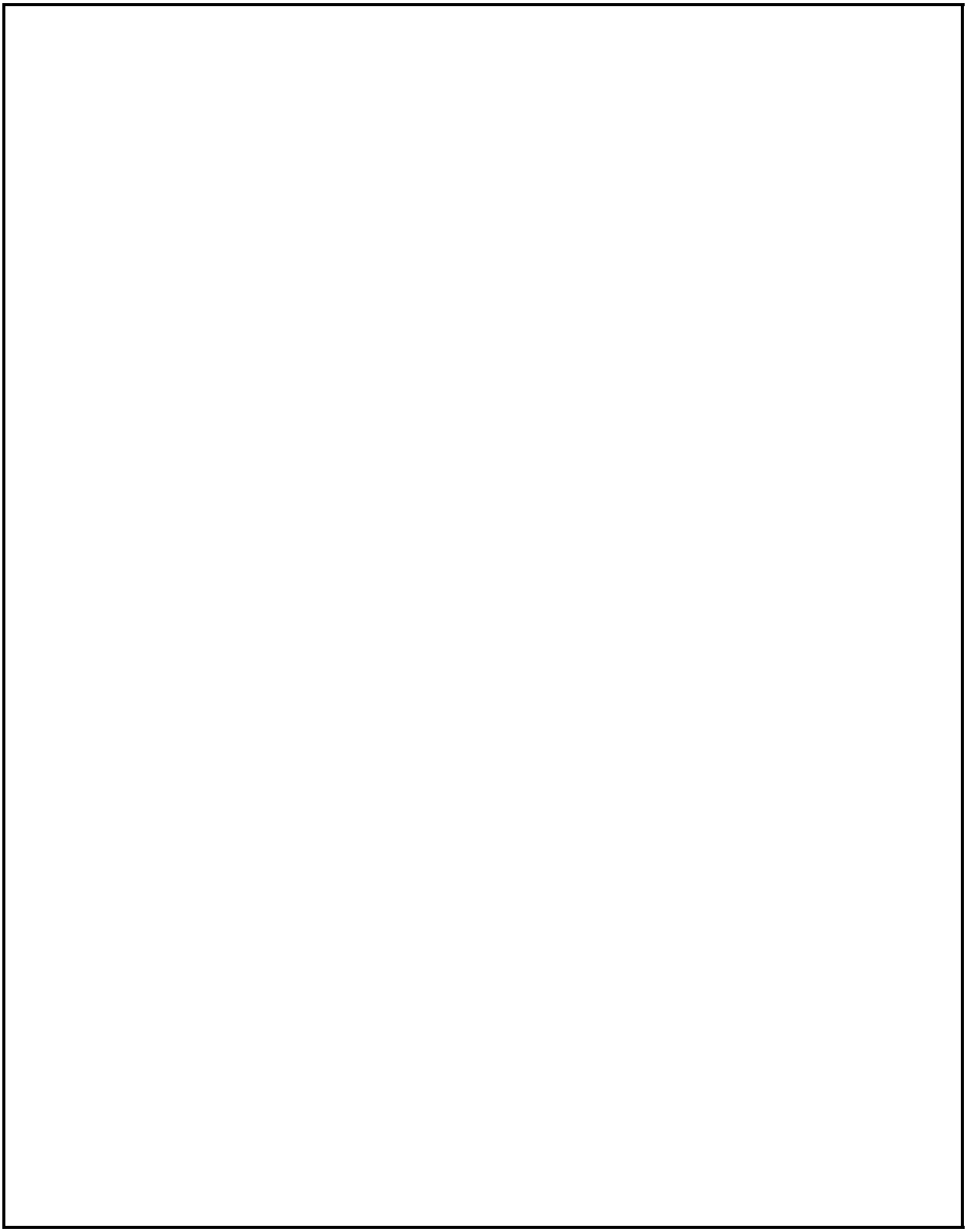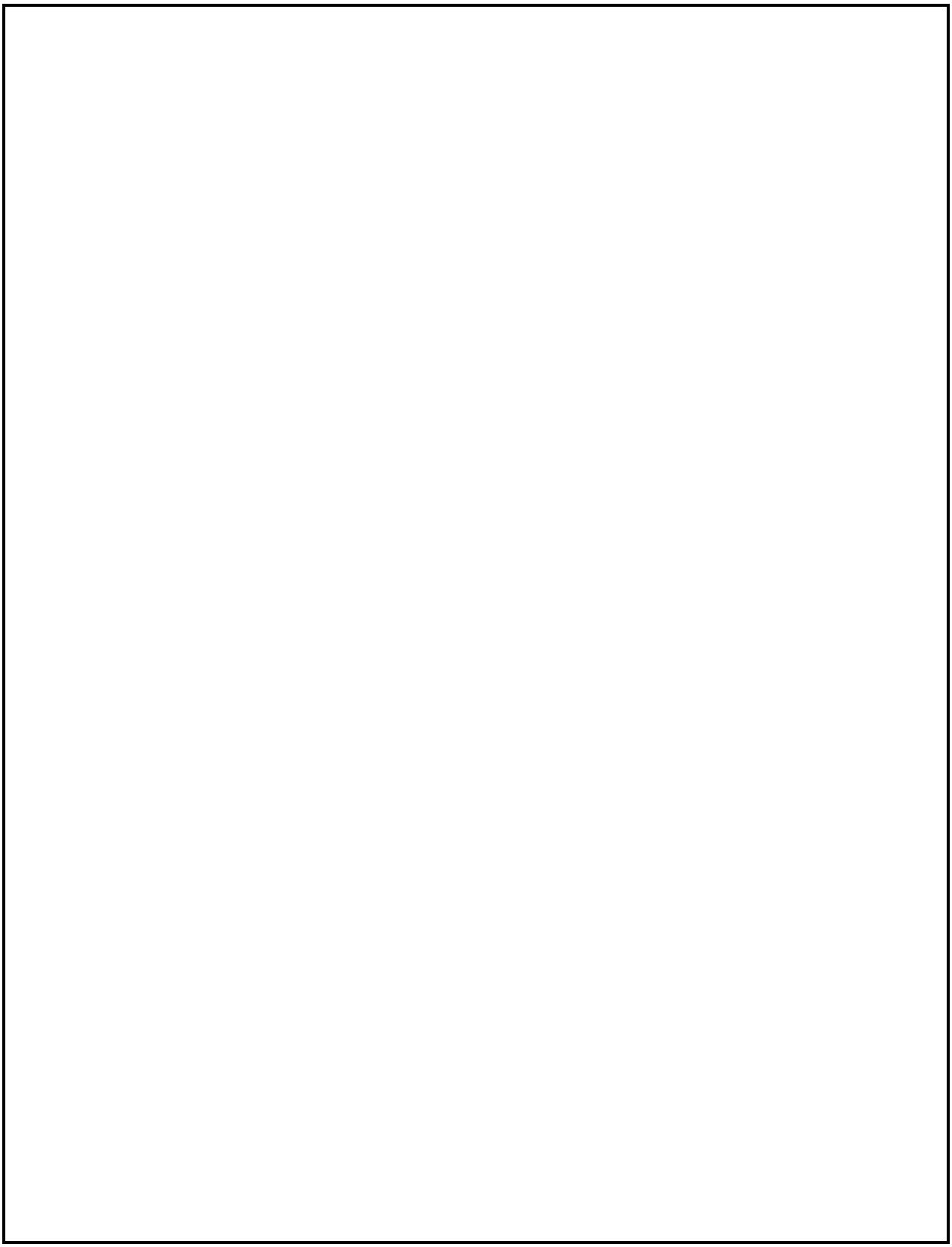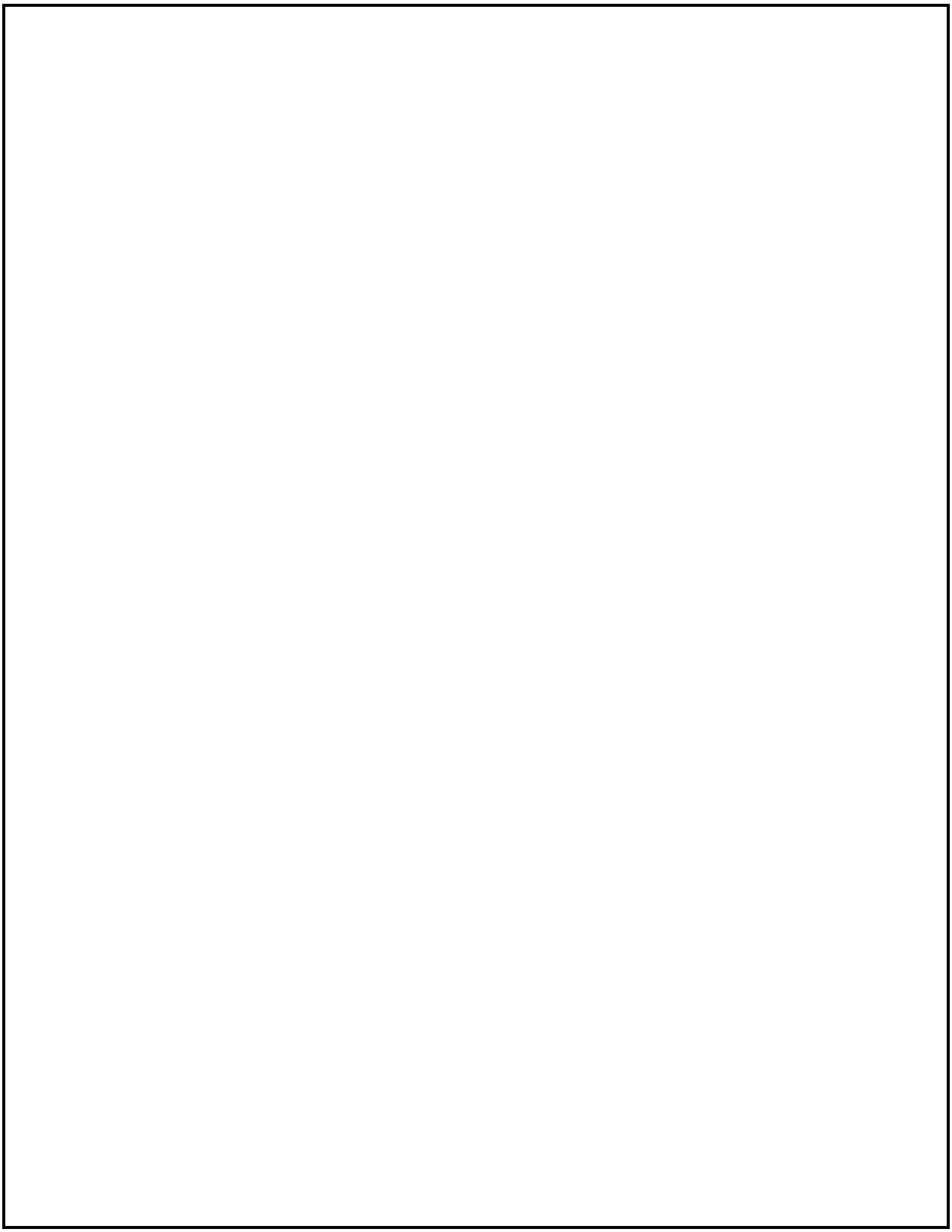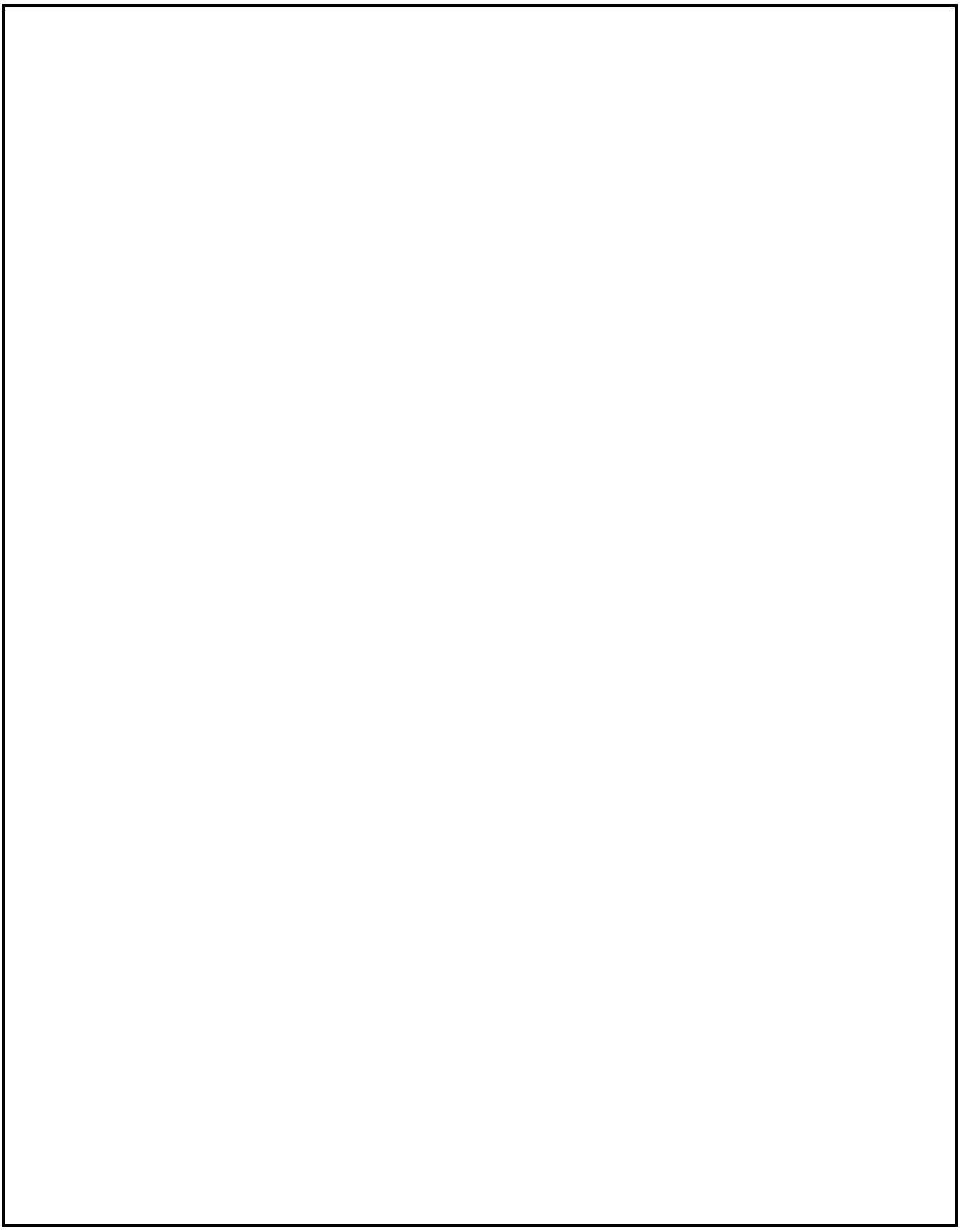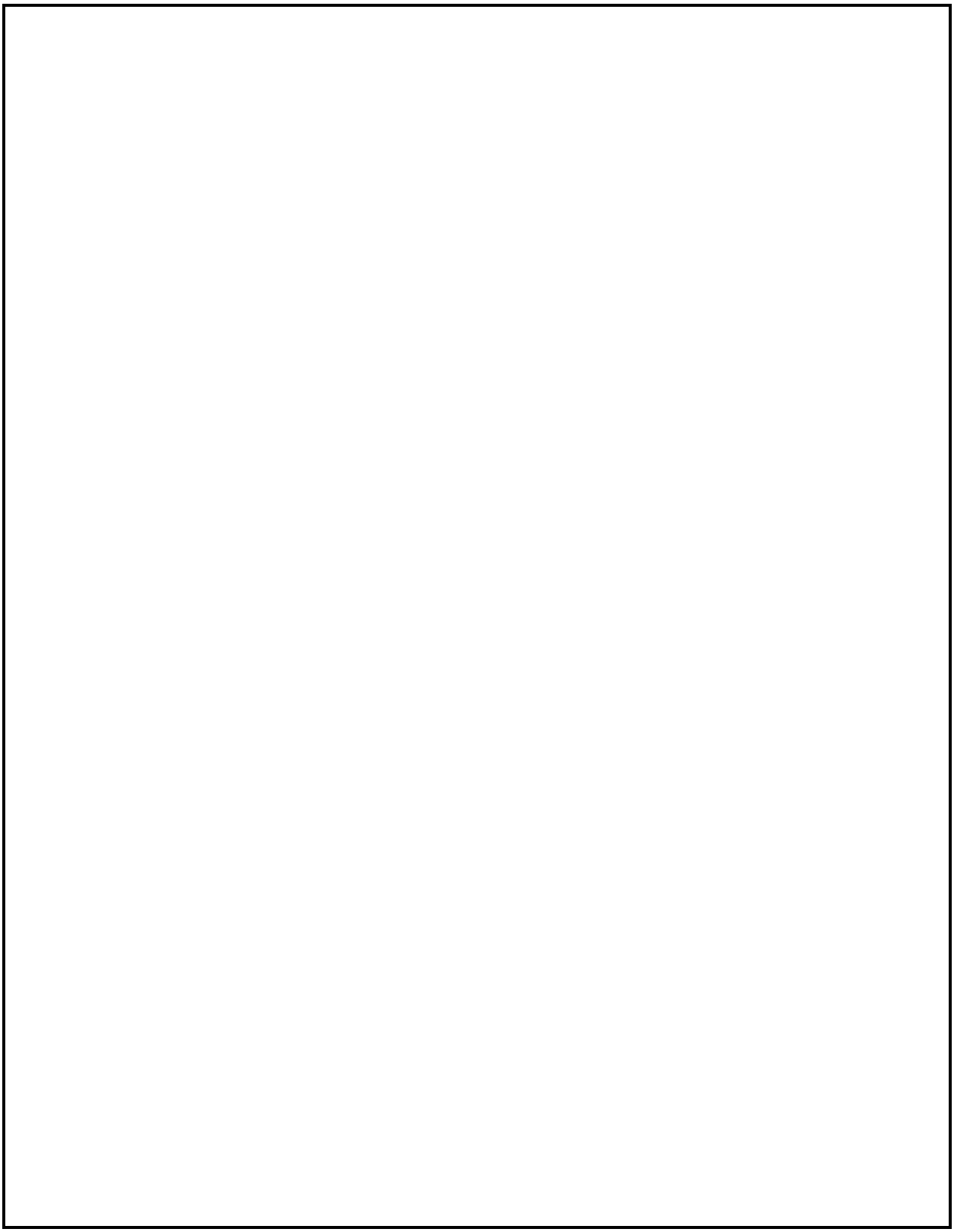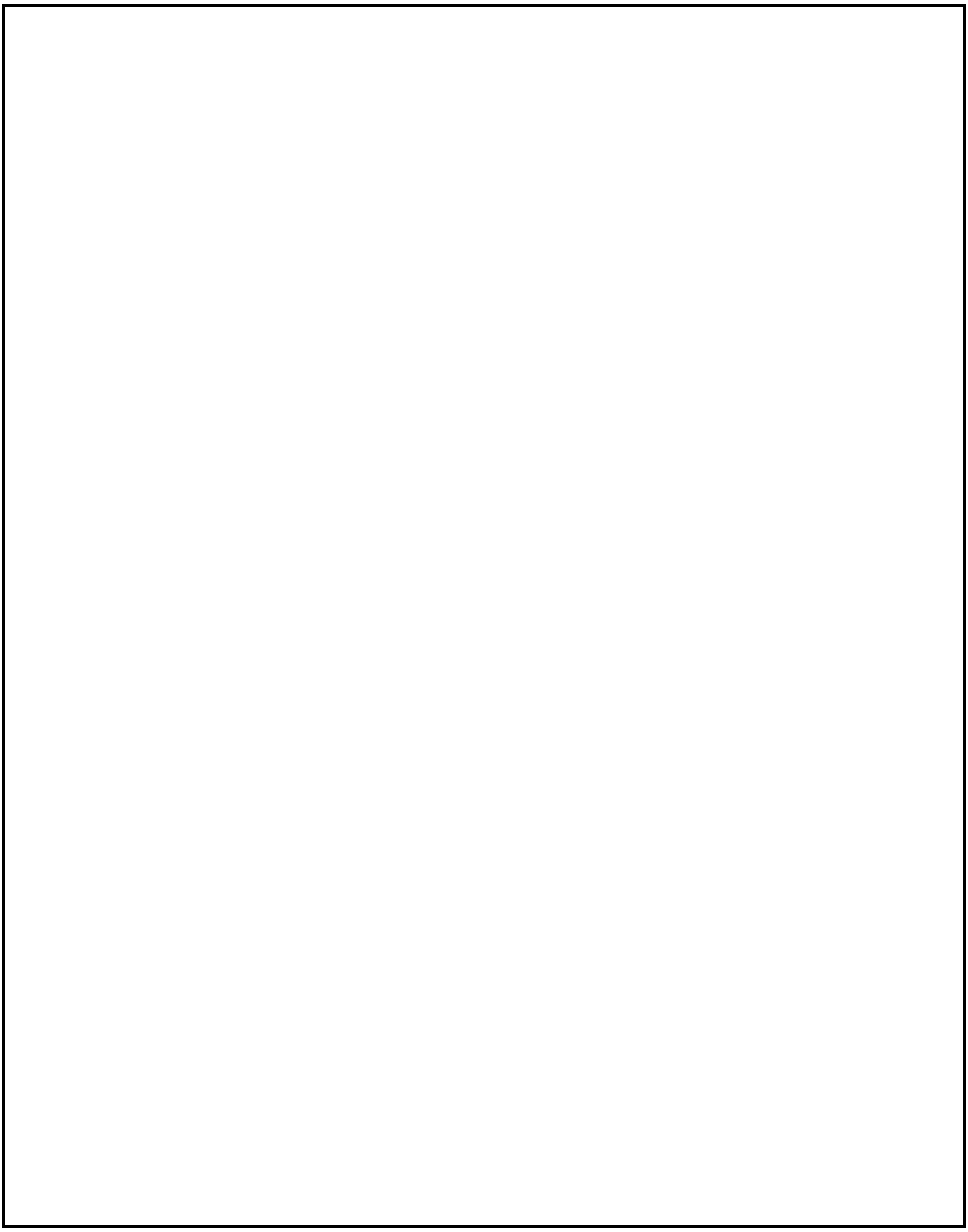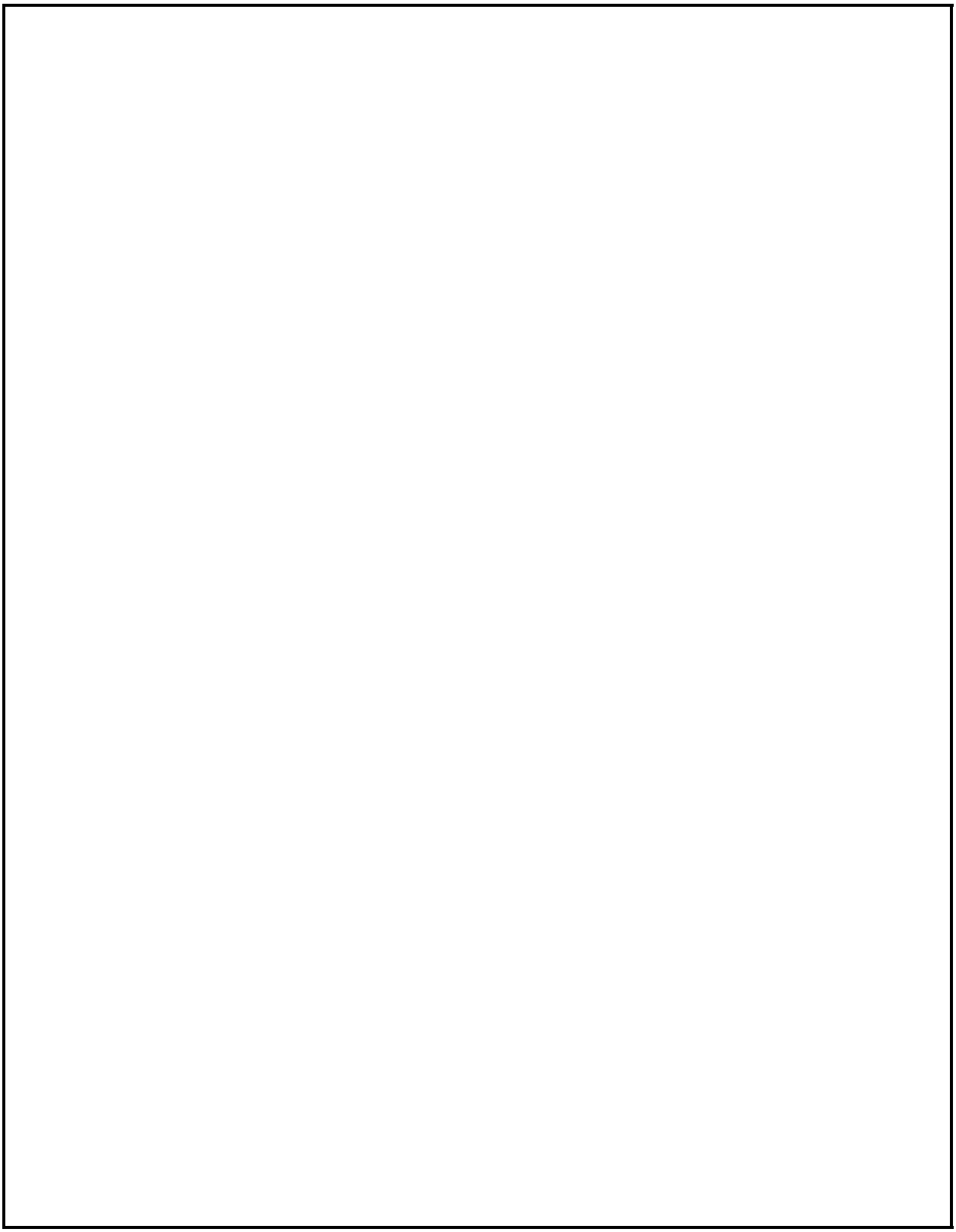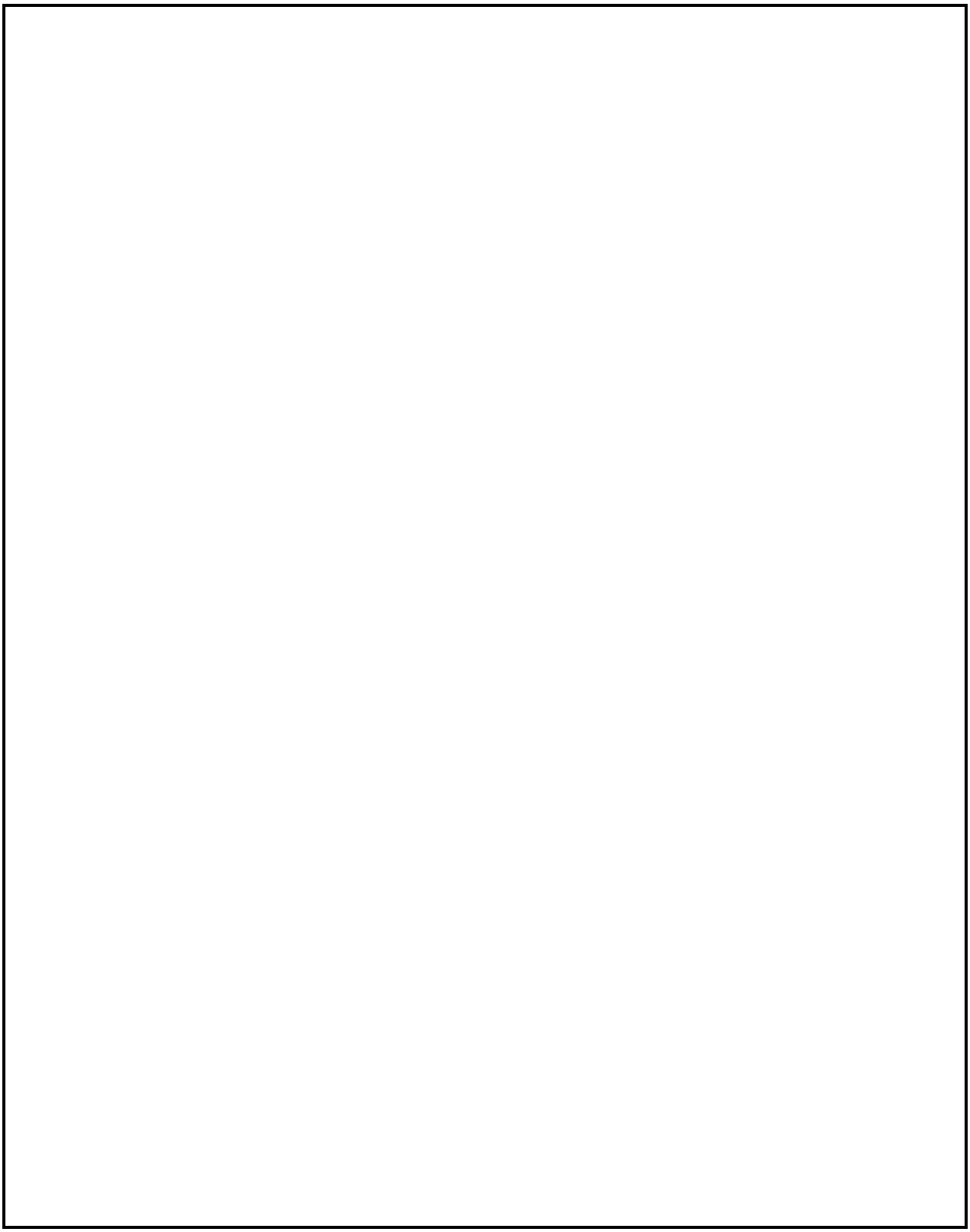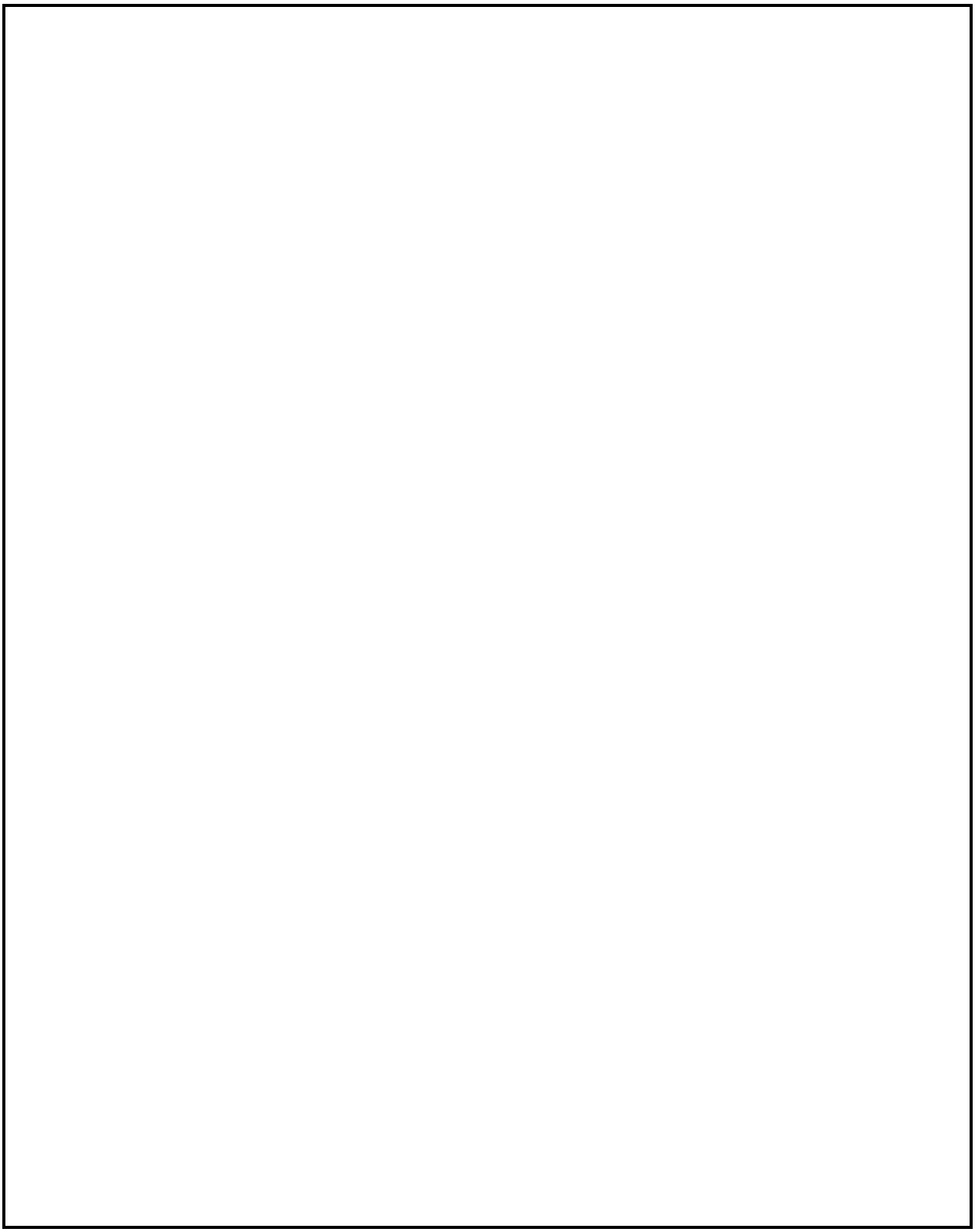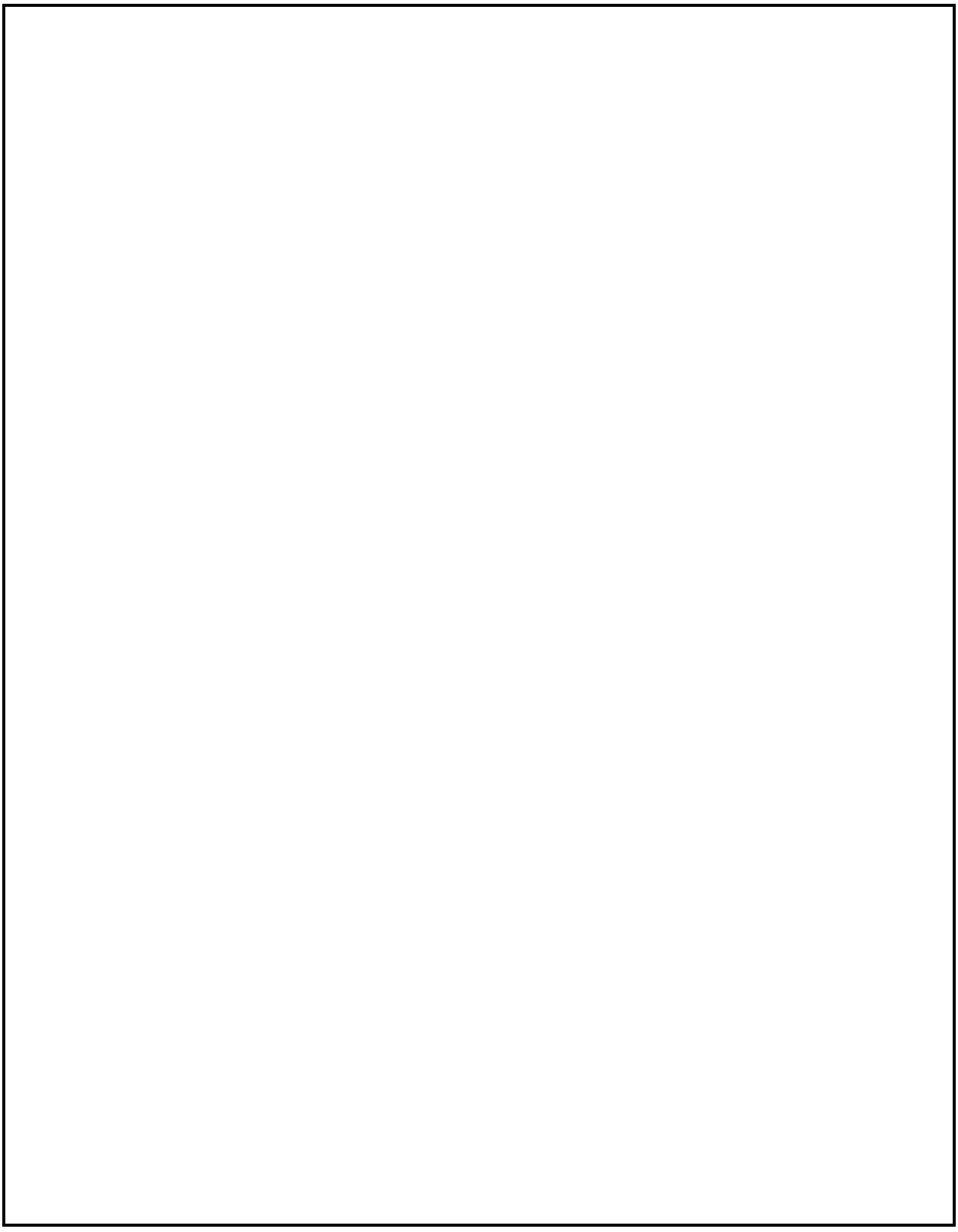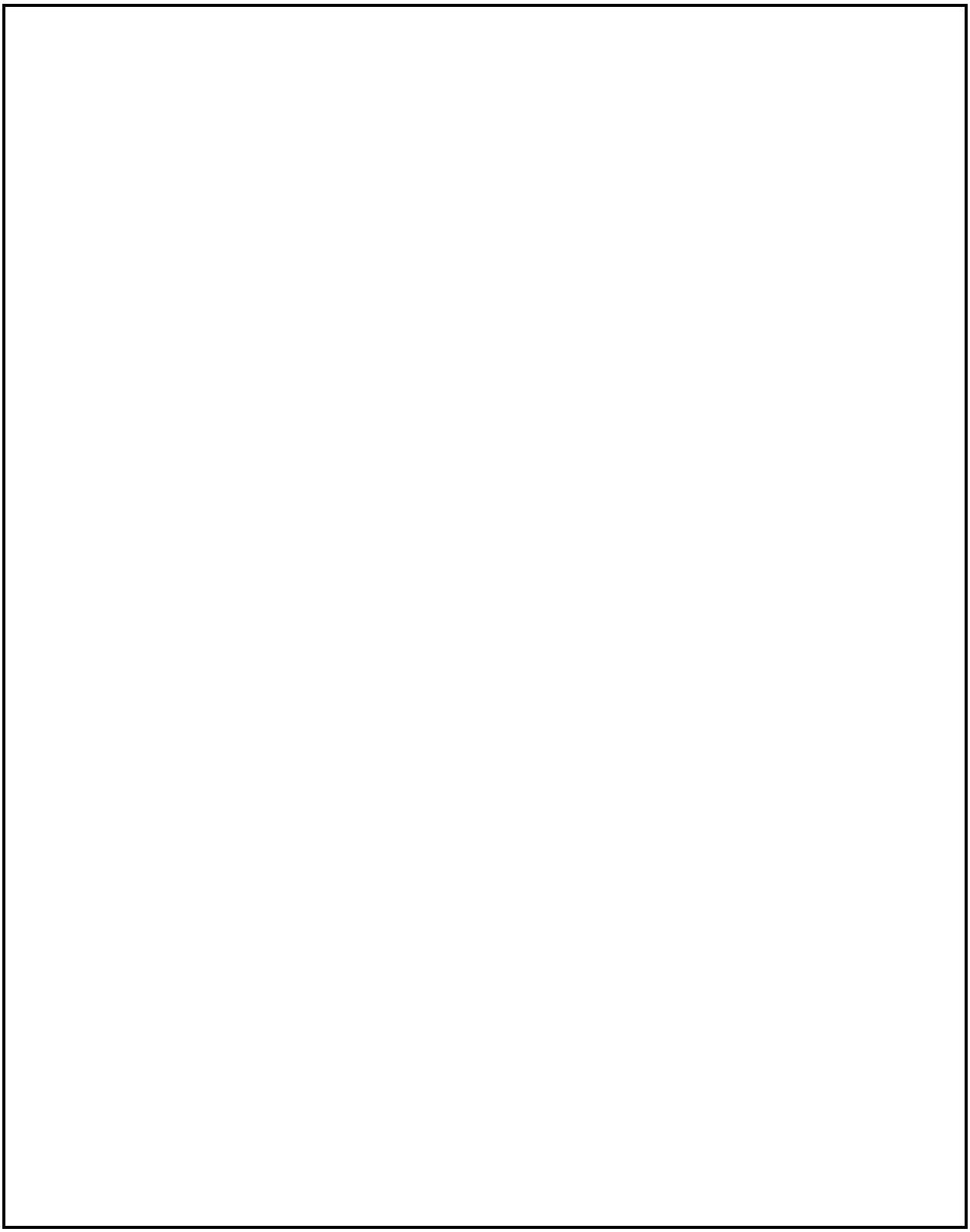
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