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Artificial Intelligence in business I: Applications, representation, acquisition and explanation*

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Abstract

The purpose of this paper is to review the use of knowledge-based systems and artificial intelligence (AI) in business. Part I of this paper examines domain applications, the use of different knowledge representations, unique contributions for knowledge acquisition from the development of systems for business applications, and models of explanation for systems developed for business. In addition, the paper discusses the use of both normative and descriptive AI systems to model business judgments. Finally, the paper provides a summary of publication sources and meetings on business systems.

1 Introduction

The use of artificial intelligence (AI) in business generally was initiated in the 1970s. One of the earliest uses of knowledge-based systems in business was Malhotra (1975). Another early application of artificial intelligence was in taxation (McCarty, 1977). Since these papers there have been many more applications and developments.

The purpose of this paper is to review that use of AI in business. This is done in a two-part paper that first summarizes many applications and methods, and second provides an analysis of some specific issues involved in the development, adoption and integration of AI in business organizations.

1.1 Scope

At one point it was feasible to discuss the entire world of AI applications in accounting or finance in a single paper. For example, O'Leary (1987) provided a relatively comprehensive review of AI in accounting as of about the end of 1985. However, the literature has expanded at a rapid pace. In an analysis of the abstracts in Brown (1989), Shanker et al. (1992) found that the number of abstracts on financial management issues alone grew from roughly one or two per year in 1977–1982, to about 70 per year in 1988. Thus, it is no longer possible to provide a comprehensive survey of AI research in business. As a result, the topics and papers chosen for review and analysis in this paper are a function of interest and their relationship to the way the author views the evolving literature.

1.2 Outline

Part I of the paper consists of seven sections. Section 2 investigates why AI in business is likely to be different than AI in other disciplines, e.g. medicine or mining. The approach in this paper is to first

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differentiate the use of AI in business from the use of AI systems in other domains. Those differences derive from concern for economics and the placement of the system in the context of an organization, and other issues. This paper also investigates some of the similarities that knowledge-based systems in business have in common with other domains.

Section 3 briefly summarizes some of the applications that have been developed in different functional areas. Throughout, references to more extensive domain survey papers are provided. Section 4 investigates some of the knowledge representation approaches used in business applications. Section 5 summarizes some of the contributions of research on knowledge-based systems in business to knowledge acquisition and explanation. Section 6 presents a summary of some of the studies of judgment using AI. Generally, the research discussed in that section extends the study of medical judgment into the context of business decisions. Section 7 presents some sources of research to facilitate finding additional and future contributions to the literature.

Part II consists of eight sections. Systems in organizations often are used to delegate expertise downward, so that the systems must be designed for non-expert users. Sections 8–10 examine specific development issues of particular interest in the design of knowledge-based systems. Section 8 analyses the use of neural networks, genetic algorithms and the careful ordering rules to ensure finding decision strategies that maximize economic return. Unfortunately, personnel at different organizational levels do not always interpret terms and situations the same as other organizational levels. Thus, section 9 examines different forms of uncertainty and ambiguity in AI systems. It summarizes the impact of ambiguous terms in the solicitation of information in management situations. There are a number of different methodologies used to develop AI systems. Section 10 investigates some of those approaches.

Sections 11 and 12 examine some integration issues with knowledge-based systems. Generally, the use of AI in business settings must ultimately be integrated with operations research (a competing paradigm for decision support) and the broader base of corporate information systems.

Sections 13 and 14 review the organizational and economic impact of AI. Finally, section 15 provides a brief summary of Part II.

2 AI in business settings

The use of AI in business is somewhat different than the use of AI in other settings. However, there are also similarities in the process of making judgments, using AI-based systems, with different disciplines. Those differences and similarities are the focus of this paper.

Despite some recent publicity there has been and continues to be substantial use of AI in business settings (e.g. Brown, 1991). Typically, successes are not always publicized for competitive reasons or because of failure. If competitive advantage is maintained using an approach, then there are generally few incentives to tell others about it. Similarly, there is little motivation to tell competitors about problem solving approaches that did not work. However, there still have been a number of applications reported in the literature. Generally, they represent reasonably successful applications that are no longer generating competitive advantage. In some cases, such as with the Barclaycard fraud detection system, publicity is thought to reduce the desire of criminals to steal the Barclaycard.

There are a number of domains of direct interest. These domains include, but are not limited to, auditing, credit systems, insurance, management accounting and taxation. Although production and production management has been one of the primary areas of system development, the scope of this paper excludes those systems since that literature alone is probably about as substantial as the subject of the paper.

Since firms can obtain a competitive advantage using tools such as AI, new AI methodologies are constantly being pursued. As a result, applications have employed a wide range of methodologies beyond typical rule-based systems, including case-based reasoning, multiple agent systems and other approaches.

AI and knowledge-based systems can provide both normative and descriptive solutions to judgment problems. However, a number of academic studies have focused on the use of AI to studydecision making in business settings. From a normative perspective, researchers have found that such systems improve judgments. From a descriptive perspective, AI has been used to model decision making processes so that those processes may be better understood.

Firms have been using operations research and management science (ORMS) and statistics for many years. Generally, ORMS is concerned with the development of mathematical or simulation models of different processes. For example, linear programming (Dantzig, 1964) has received substantial use. As a result, AI faces competing and contrasting models. Thus, we might expect the potential integration of AI and ORMS in many business situations.

Firms have established computer-based management information systems. Substantial departments exist concerned solely with the generation and processing of information for managerial consumption. As a result, AI comes into an environment where there is already an existing base of computer expertise, models, systems and flows of information. As a result, it is unlikely that in the long run there will be many stand-alone AI applications that are not integrated into the basic management information system, or those that do not consider the existing information systems environment.

Businesses are organizations, and systems developed for their use must function in organizational settings. For example, AI has been used to facilitate the downward delegation of certain judgment tasks. Thus, there are organizational issues that must be addressed when we consider the adoption of AI, and there are construction issues for the development of systems for applications, deriving from the business context.

In addition, since managers delegate decisions downwards, this has resulted in the need to address issues in the construction of systems to ensure that non-expert users will generate the appropriate solutions. These issues include the generation of good heuristic solutions in real time.

Business relies on an economic model for analysis and evaluation, thus there is some concern about issues such as creating value with AI and how to determine whether an AI application is cost-effective. Management speaks a certain language—as a result, it is critical that developers and designers consider many of those same issues.

The remainder of this paper focuses individually on each of these and other issues to study the use of AI in business.

3 Applications

There have been a large number of AI applications in business settings reported in the literature. These applications have been developed by both academics and practitioners. In most application settings, those systems have been developed to assist judgment tasks in a number of areas, including the following.

3.1 Auditing

External auditors issue an "opinion" about the financial statements. That opinion directly influences the credit of the firm and the ability of the firm to generate capital. There have been a large number of systems developed to assist auditors in the audit process (e.g. Brown, 1991). In addition, auditing has been the subject of substantial research about auditor judgment. Systems have been built modelling the audit planning process, auditing advanced EDP systems, auditing the amount of bad debts expected, and many other applications. There have been a number of surveys on the use of AI in auditing, including, for example, O'Leary and Watkins (1989).

3.2 Credit and loan systems

Credit and loan decisions are made both by banks and consumer credit agents. Duchessi et al. (1988) developed a system designed to assist commercial loan officers in determining whether or not medium or large size companies would be recommended for a loan. American Express's "Authorizor's Assistant" helps with the determination of whether or not a credit purchase will be permitted (Newquist, 1987). A survey of some other financial applications is provided by Holsapple et al. (1988).

3.3 Insurance

AI has found application in the insurance industry in a number of areas including administration, claims control, claims processing and underwriting, with the primary use falling into the area of underwriting. A survey of insurance expert system users and developers is found in Wright and Rowe (1993), while a recent review paper by Rowe and Wright (1993) summarizes much of the literature.

3.4 Internal auditing

Internal auditing is concerned with the efficiency, effectiveness and security of management and systems. There have been a number of different systems developed for these purposes. For example, Tenor (1988) describes a system designed to determine if the user of a credit database is a legitimate user. Brown and Phillips (1991) and O'Leary and Watkins (1989) provide reviews of some implemented internal auditing systems.

3.5 Management accounting

Management accounting includes the use of accounting numbers to manage companies and the process of budgeting. An important example of that process is "variance analysis". In variance analysis, there is a set of expectations about how much something should cost. If the actual costs are different to the expectations, then we have to decide whether we should investigate. An expert system has been built for this task (Hollander, 1992). Brown and Phillips (1990) summarize the contributions of a number of different management accounting expert systems.

3.6 Personal financial planning

Personal financial planning systems typically include a broad base of knowledge. For example, a system might include accounting, investment, law, regulations and tax knowledge. Different systems have been designed for professional and financial planning experts and for general users. Phillips et al. (1990) note that the Personal Financial Analysis system developed by Price Waterhouse can provide financial planning guidance to its employees, including the impact of the company's benefit plans.

In an analysis of four different financial planning systems, Brown et al. (1993) found many differences between systems designed to do the same task for the same user. For example, Phillips et al. (1990) report that the assumptions of the different financial planning systems can result in substantially different financial plans, given an attempt to provide the same inputs. Brown et al. (1990), Humpert and Holley (1991) and Phillips et al. (1992) survey of the use of expert systems in personal financial planning.

3.7 Tax

The heavy reliance on rules and cases makes tax an area amenable for the use of AI. As a result, there have been a large number of systems developed to assist in the solution of tax problems. Users of AI technology in tax include the Internal Revenue Service, the government organization in charge of collecting taxes in the United States and virtually all of the large accounting firms. Virtually all aspects of tax have been the source of AI applications including both tax form completion and tax planning. Survey papers include, Michaelson and Messier (1987), Brown (1988), Brown and Streit (1988) and O'Leary and Karlinsky (1990).

3.8 Trading systems

Perhaps the domain with the biggest potential payoff is that of systems designed to assist in stock or commodity trades (e.g. Tyagi, 1987). Potentially, a single transaction could make millions of dollars. Although there are reports of different systems (e.g. Byrnes et al., 1989), generally systems that are effective are not discussed in the literature, since such discussion is likely to limit future success. In addition, although there are reports of uses of AI for trading, there are also reports of many of those systems not being used for various reasons, including changes in hardware or software or just because they are not useful. The usefulness of these systems might be subject to question because the knowledge on which they are based is not subject to consensus (e.g. technical analysis or charting), or because the systems are not designed in a manner that is consistent with trading organizations (e.g. investment bankers decide "we have this stock to sell, now who we should sell it to . . .). A brief review of some trading systems is provided by Holsapple et al. (1988).

3.9 Security and fraud: Intrusion-detection systems

AI has been used in a number of related domains to try to determine the existence of anomalous or fraudulent transactions. These systems have their origin in so-called "intrusion-detection" systems (e.g. Denning, 1987; Tenor, 1988). These are systems designed to determine if a computer has an intruder. There are a number of applications of these types of systems. Tenor (1988) described a system used to protect a credit database from illegitimate users. Lecot (1988) describes a system designed to determine if ATM users are legitimate. Further, AI has been used to monitor trade transactions for "unusual" activity (e.g. Byrnes et al., 1991). A survey and extension of methodologies of intrusion-detection systems is provided in O'Leary (1992c).

3.10 Other applications

Additional applications include marketing (e.g. Rangaswamy et al., 1987, 1992), portfolio analysis (e.g. Holsapple et al., 1988), project management systems (e.g. Bimson et al., 1992), telex routing systems (e.g. Goodman, 1991), corporate financial planning systems (e.g. Kastner et al., 1986), knowledge discovery (e.g. Anand and Kahn, 1992) and help desk applications (e.g. Kass and Stadnyk, 1992).

4 Knowledge representation

The purpose of this section is to briefly discuss some of the forms of knowledge representation proposed or used to solve problems.

4.1 Rule-based reasoning

One of the first approaches used to build AI models was the rule-based approach. Michaelson (1982) developed one of the first business systems to solve tax problems. In particular, the system did tax planning for individuals. The rule-based nature of much of the tax law suggested that many tax problems could be solved using rule-based expert systems.

Dungan (1983) developed what was probably the first system in auditing. The system (*Auditor*) was designed to solve the problem of determining whether or not a bill was collectable. Although that system has been criticized for a variety of reasons, its use of rules was soon followed by other expert system developers in the auditing community.

Rules have been found to be quite useful in a number of situations. However, it was found that experts did not "think" using rules and that experts in some cases had substantial difficulty creating rules (Biggs et al., 1987). As a result, it became necessary to find alternative models that more readily provided models of human information system processing.

4.2 *Case-based reasoning*

Much of the previous research and development work has hinted at the use of case-based reasoning. However, it was not until recently that case-base rule-based approaches have been directly used in business applications. Even at this point, only a few applications, using case-based reasoning, have appeared in the literature. They include applications in accounting, auditing and tax.

O'Leary (1992a) discussed the use of case-based reasoning in an accounting domain where case-based reasoning dominates: legal regulation. In that domain, characteristics of court cases form the basis of the reasoning used to make decisions.

Denna et al. (1992) developed a case-based system for use in audit judgment. The concern was with the modelling of an auditor's judgment as to whether there had been a material error in the net income computation. The scope of the system was aimed at errors that occurred due to problems with the firm's inventory. That system used cases that had slots for client, status of the change in inventory (same, increasing, decreasing), a set of operation events (e.g. order inventory or receive inventory), direction of change of net income due to the events, and other situation characteristics.

Varghese and Turner (1992) presented a tax-based system that used case-based reasoning. The focus of their research was on the organization of knowledge about legal tax cases. Case attributes include the name of the case, the date, the involved parties, outcome and other characteristics.

4.3 *Bayes' nets/influence diagrams*

Generally, expert systems use heuristic procedures for processing weights and/or probabilities on rules, neglecting the interaction between conditional probabilities. Bayes' nets (or an extended version of Bayes' nets, influence diagrams) provide an approach that uses those conditional probabilities to relate sets of events using conditional probability arguments (for an excellent introductory discussion see Edwards, 1991). Bayes' nets can be used to represent most decision problems that can be represented in decision trees. Evidence and events are represented as nodes. Influences are captured using arcs. Bayes' nets still require substantial assessment of conditional probabilities, however, once those probabilities have been gathered, there are Bayes' net shells (software that facilitates the development of Bayes' nets) that do the computations and facilitate model development.

Bayes' nets have been used extensively on legal problems (e.g. Edwards, 1991) and on medical problems (e.g. Heckerman, 1992). However, there has been limited application of influence diagrams and Bayes' nets to accounting, finance or general management problems. O'Leary (1993) provides an overview of the use of Bayes' nets and influence diagrams in accounting and auditing. There also have been a number of extensions to influence diagram using alternatives to probability theory. For example, Srivastava and Shafer (1992) use a belief function approach to model the relationships between audit events.

4.4 *Multiple agent systems*

Multiple agent systems seem to have received only minimal investigation, as a vehicle to model business problems. O'Leary (1991, 1992a) has discussed the use of multiple agents in some accounting systems and databases. Chang et al. (1992) provide a distributed reasoning approach to model the process of multiple auditors cooperating in the analysis of the reliability of the controls in an accounting system. Raghupathi and Schkade (1992) investigated the use of a blackboard system to model the process of whether or not to pursue litigation. Pinson (1992) developed a multiple agent system to assist in the credit evaluation process.

4.5 Machine learning

A number of approaches to machine learning have been used by researchers, including genetic algorithms, inductive learning algorithms and neural nets. Genetic algorithms were used by Greene et al. (1992) in an attempt to determine what entities to audit for sales tax compliance to find those with delinquent tax payments. Bauer and Liepins (1992) also used genetic algorithms to generate profitable stock market trading strategies. Messier and Hansen (1988) used inductive learning in the prediction of bankruptcy. Shaw and Gentry (1988) used inductive learning to evaluate whether a loan should be given. Neural nets have been used for a wide range of tasks including predicting bankruptcy (Chung and Tam, 1993), forecasting (Jhee and Lee, 1993) and auditing (Coakley and Brown, 1993).

4.6 Natural language reasoning

There has been some research on natural language in accounting, finance and management. Generally, two basic approaches have been used: building general understanding capabilities, and exploiting specific domains.

Goldstein and Storey (1991) have developed the "commonsense business reasoner". The system was built as a prototype of the kind of tools that could be embedded in other systems to provide those systems with the ability to understand the business world. Their approach uses developments from "naive semantics" (Dahlgren, 1988) to develop semantic network models of frames. The commonsense business reasoner is based on a generic model that includes knowledge of the manager, employee, owner, enterprise, facility, product and consumer. There are a number of different operators on the arcs connecting those concepts, including "is-a", "has", "owns", "makes", "buys" and "sells".

O'Leary and Kandelin (1992) developed a system that included understanding of accounting transactions based on a qualitative model of information content. The system used a predictor-substantiator approach employed in FRUMP (Schank, 1978). For example, given the statement "supplies were purchased . . ." the system immediately knows that amount of supplies will increase, and that the firm will owe money to someone. It anticipates that information about an agent will follow in the remaining discussion, otherwise default information will be employed. The system anticipates and then makes predictions. If its predictions are unsubstantiated then it goes back to make additional predictions that are substantiated. The system's understanding is based on models of the accounting domain.

Perhaps the primary consumer of natural language systems is the banking industry. The development of a system by a major bank is discussed in Sahin and Sawyer (1988) and a survey of a number of banking applications is provided by Harris (1992).

5 Knowledge acquisition and explanation

The development of intelligent systems for business applications has also led to a number of developments in knowledge acquisition and explanation.

5.1 Knowledge acquisition

First, the development of business systems has led to a number of unique approaches to knowledge acquisition. For example, knowledge acquisition for ExperTAX (Shpilberg and Graham (1986, p. 79) led to the following approach:

> "A conference room with a long table in the middle was divided by a curtain. All the . . . information was gathered and deposited on the left side of the table, including the forms and questionnaires deemed

> relevant. A staff accountant with no previous experience . . . (with the task) was asked to sit at the left side of the table. Two experienced . . . people were given blank questionnaires and forms and were asked to sit at the right side of the table, separated by the curtain from the staff accountant and the case data.
>
> The staff accountant was informed that it was his responsibility . . . (to solve the problem) for the client. He was told that he currently had all the necessary information in front of him and most importantly, a panel of experts behind the curtain. The experts were told that it was their responsibility to guide the staff accountant to the successful . . . (solution of the problem). They were instructed to actively guide him with verbal advice and to answer questions when asked. They were unable to go to the other side of the curtain to explain . . . .
>
> The process was videotaped with two cameras and observed by the knowledge engineering team. Several variations of the process were conducted . . . over three days."

Another approach used by O'Leary and Watkins (1991) also provided a unique approach to knowledge acquisition. A system was to be developed to assist diagnosticians' ability to answer questions that were called in. The first approach was to visit the site, listen in on 'phone calls and tape record the solution approach used by the diagnosticians. However, that approach was found to be obtrusive. Diagnosticians were reluctant to indicate when a problem, within the scope of the system being developed, was called in. Thus, the second approach was to allow the diagnosticians to tape the calls themselves without the obtrusive presence of observers. However, it seemed that the tape recorders did not work once the knowledge engineers left the premises. No 'phone calls were tape recorded by the diagnosticians. As a result, a third approach was ultimately employed with the permission of management. The knowledge engineers developed "scripts" that were then used to call in questions to the diagnosticians in an effort to assist in the knowledge acquisition process. Those conversations were taped and used as the basis of knowledge acquisition for the system. That final approach was useful, since it facilitated the manipulation of the decision variables in the scripts and was completely nonobtrusive. This unobtrusive approach was thus used to generate protocol analyses.

Second, the importance of existing documentation in the development of systems is apparent with the development of knowledge-based systems in business. Much base knowledge in organizations is captured in documentation. In other settings the use of documentation does not seem to have generated interest, but is apparently important in business situations. Unfortunately, documentation is rarely in a usable form and generally is not used. However, rule-based systems have proved to provide a medium for generating a usable version of documentation (e.g. O'Leary and Watkins, 1990, and others).

Third, although some researchers have studied to find the "best" approach to knowledge acquisition, the development of business systems has led to the finding that a portfolio of methods is the "best" approach (e.g. O'Leary and Watkins, 1990). Typically, the development of an intelligent system to solve problems, generates knowledge from documentation, observation, interview and other approaches, like those discussed above. No one approach generates all the necessary knowledge. Each activity generates additional, and often complementary knowledge. To not use one of those three basic approaches is to potentially ignore a major source of knowledge about a given process or set of judgments.

5.2 Explanation and model-based reasoning

Explanation has also received substantial attention. Perhaps the approach that has received most interest is that of Kosy and Wise (1984). Their research focused on the task of "explaining results". Typically, the user of a financial system is faced with a set of financial statement numbers, including sales, profit and unit costs. The questions of interest might then include (Kosy and Wise, 1984) "why do sales go down?" or "why does unit cost go up?" Those researchers found that a classic MYCIN-like trace of the rules was inappropriate for explaining.

Instead, they developed a "company model" that represented activities in terms of quantitative relationships between the financial variables. The model consisted of three types of formulas. First, there were exact formulas, for example "sales = volume × sales price". Second, there were approximations that were used to estimate complex relationships of endogenous variables. Those formulas were intended to yield the aggregate effect of complex causal processes, for example, "operating expense = 0.15 × gross sales". Third, there were assumptions; for example, the company model needed to include an inflation rate.

The company model was used to analyse results and generate associated explanations along a number of different dimensions. First, the reference point depends on the basis of comparison. For example, if the question is "why did sales go up this year", that relates the current year to previous years. Second, there are implicit referents. For example, the question "why is gross margin so small?" relates to, for example, the average change in gross margin. Third, in some situations there is concern over specific intervals; "Why did sales go up in 1984–1988?" Fourth, a user might phrase a question such as "Why did y change?" In this case, the system needs to refer to directions in magnitude, providing specificity when inferred by the user.

The system provided explanation by going through the following five steps: it interpreted the question; identified the significant effects; the effects were characterized qualitatively; an answer was expressed; and finally the explanation was continued if desired.

Experimentation by Kosy (1989) provided a number of findings. First, generally only a few variables account for the differences to be explained. Second, the variables form a natural hierarchy based on the formulas.

More recent research (such as Hamschler, 1989, 1991) has focused on the models on which such explanations are based. Those models are based on models of the firm, such as those in Helfert (1986) and others. An extended survey of this research is provided in Hamschler (1992).

6 Normative and descriptive models of human behaviour

AI has been used to develop both normative and descriptive models of human behaviour in business domains.

6.1 Normative models: AI helps generate better decisions

It is apparent from the number of AI systems that have been developed and continue to be used that those systems can be helpful in generating better decisions. As a result, there is substantial indication that AI provides important normative models for human behaviour. However, there also has been direct research on the ability of AI to help the user generate better decisions. Back (1991) developed an integrated AI and OR system using linear programming and logic to help solve a set of Finnish tax problems.

After the model was developed, Back (1992) performed substantial testing to determine whether the model helped the user make better decisions. The experiment used senior students as subjects, since in business settings the use of AI systems if often delegated downwards. A total of 120 problems were solved with a textbook as the guide, and 96 problems were solved with the expert system model as the decision support tool. Only 53% of the textbook supported problems were correctly solved, whereas 98% of the expert system supported system were correct. As a result, it can be seen that the use of the system had a major impact on the quality of the decisions generated.

6.2 Descriptive models of individual judgments

One of the primary academic activities in the study of AI in business is the use of AI to generate models of judgment. Outside research in medicine, it appears that much academic judgment research has focused on audit judgment. Apparently similar judgment tasks occur in a number of domains, for example granting loans, granting credit, trader judgment, etc. However, behavioural and cognitive research seems to be more a part of the academic heritage of accounting and auditing than other disciplines such as finance and insurance.

Efforts aimed at developing cognitive models of judgment include Meservy (1986), Selfridge and Biggs (1990) and Peters (1992). These systems generally are model-based, where the models are derived from discussions with experts in the particular domain.

The model developed in Meservy (1986) was a cognitive model of auditor judgment. The development of the model included substantial testing concerning the cognitive features of an AI system as compared to human experts. For example, tests compared the system and experts as to percentage of time spent in "information acquisition" (read, data search, etc.), "planning", "analytical activity" (conjecture, inference, etc.), and "action" (generate alternatives, decision, etc.). It was found that the system seemed to exhibit behaviour that was cognitively similar to the judgment of human experts (e.g. O'Leary, 1992b).

The model presented in Selfridge and Biggs (1990) was modelled to judge whether a company would be expected to continue or if it would probably fail (going-concern problems). The system employed general financial knowledge and eight other types of knowledge, including, knowledge of: actual events, normal events, company function, company markets, industry, multiple business lines, changes over time and other companies. This knowledge was used in a four phase plan designed to first recognize the existence of going concern problems, understand the cause and evaluate management's plans to address the problem.

7 Sources of research on AI in business

The literature on the use of AI in business continues to grow, with alternative AI approaches being used to solve a growing base of problems. There are a number of sources where these applications and new technologies are discussed.

First, there are a number of recurring sources of publication of applications. The American Association for Artificial Intelligence (AAAI) sponsors and publishes *Innovative Applications of Artificial Intelligence* each year. The quarterly journal *International Journal of Intelligent Systems in Accounting, Finance and Management* specializes in the use and application of AI in business settings.

Second, there are a number of books of readings and textbooks that focus on expert systems and artificial intelligence in business. Silverman (1987) was one of the first books in the area. More recently, Liebowitz (1990), Chandler and Liang (1990), O'Leary and Watkins (1992) and Watkins and Eliot (1993) provided books of readings on the use of AI in a number of situations. These books and the recurring sources of AI publications provide most of the resources for this investigation.

Third, there are a number of meetings each year that specialize on the use of AI in business settings. The AAAI meeting for each of the years 1990–1993 has included workshops on AI in Business (sponsored by the AAAI special interest group "AI in Business"), in addition to "Innovative Applications of Artificial Intelligence" meetings.

The oldest individually sponsored, continuously held meeting focusing solely on AI in business is sponsored by the School of Accounting at the University of Southern California. In 1993 it will be held at Stanford University, in conjunction with the Intelligent Systems Laboratory in Engineering Economic Systems at Stanford. The *IEEE Conference on Artificial Intelligence Applications* (CAIA) also solicits application papers. In addition, the conference *AI in Economics and Management* has been held three times over the last ten years. In 1993 it will be held in Portland, Oregon.

The American Accounting Association (AAA) has a special interest group, "AI/ES in Accounting". That group has been active in sponsoring symposiums on the use of AI in accounting. At the AAA national meetings in 1992 and 1993 there were symposiums on the use of AI in accounting applications. In addition, there have been recurring conferences such as "AI on Wall

Street", and "AI in Insurance" in the United States, and "An Analysis of Expert Systems in the European Banking Industry" held at the Universita Cattolica in Milan, among others.

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