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Dana A. Madalon

Frederick W. Rook

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Discussant's Response to "Expert Systems and AI-Based Decision Support in Auditing: Progress and Perspectives"

Dana A. Madalon
Frederick W. Rook
Price Waterhouse

1. Introduction

A critical issue affecting progress in the development of AI-based decision support systems for auditing is the relationship between *research* and application *development*. In order to present our view of the relationship between these two concepts, it is useful to first discuss our perspective and background in both AI technology research and expert system development.

As AI technology researchers, we have conducted research in knowledge acquisition, knowledge representation, natural language analysis and understanding, planning and design, and computational theory. For example, we have examined and advanced the use of constraint satisfaction problem formulations as a method of inferencing. We recognize the extent to which the state of AI technology is driven by research in the areas of computer science, computer engineering, cognitive psychology, decision sciences, operations research, human factors engineering, and mathematical logic. To ensure the most effective use of these technical developments to the applied realm, we have worked closely with a number of leading AI researchers. These include Dr. Robert Wilensky at the University of California Berkeley AI Research Center, Drs. Judea Pearl and Rina Dechter at the Cognitive Systems Laboratory of the University of California Los Angeles, Dr. Drew McDermott at the Yale University AI Project, Drs. B. Chandrasekaran and John Josephson at the Ohio State University Laboratory for Artificial Intelligence Research, and Dr. Andrew Sage at the George Mason University School of Information Technology and Engineering.

As expert system developers, we have designed, developed, and implemented over thirty prototype and operational expert systems in a variety of application areas. Our expert systems have addressed such problem types as monitoring, diagnosis, assessment, risk analysis, resource allocation, scheduling, and planning. While we have successfully fielded operational expert systems, we have also met technological hurdles too great to be overcome with today's technology. The foundation of our success in building expert system applications is the ability to leverage existing AI technology, i.e., technology that in many cases has been effectively transferred from university settings.

One of the greatest challenges facing both academia and industry is the effective ***utilization*** of AI research results. Too often research results fail to be incorporated into the mainstream of application development. This paper briefly identifies some of the reasons why. The overall goal of the paper is to provide an industry perspective on several issues identified in the paper by McCarthy, Denna, and Gal [1990]. In Section II, we discuss our view of the difference between research and development. In Section III, we discuss the issue of bringing research results to bear on real-world problems. In Section IV we present a view of how academia and industry should work together. Finally, we briefly summarize our view of the future of AI in accounting in Section V.

2. Relationship of Research to Development

The McCarthy et al. paper focuses considerable attention on the relationship between research and development. The central issue in examining research and development is defining the relationship ***between*** the two processes. Research in AI provides a technological foundation upon which real-world applications can be developed. This relationship is depicted in Figure 1.

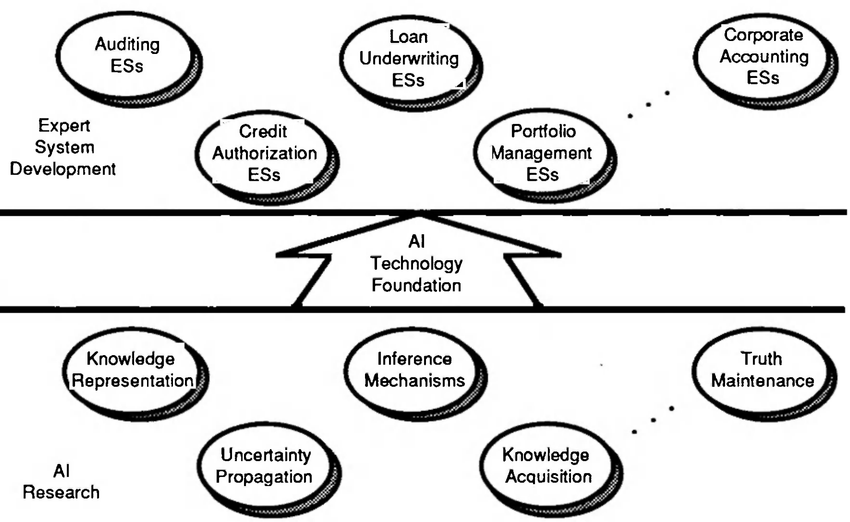

Figure 1. The Relationship of Research to Development

The task of classifying a program into either research or development is not a difficult one. Research advances the technology by yielding techniques, methods, models, or approaches that may be applied to a variety of information processing requirements. For example, AI research in knowledge representation has yielded such concepts/paradigms as production rules, frames, scripts, and so forth; research in inference techniques has yielded pattern matching algorithms, diverse search strategies, control mechanisms, etc.; research in truth maintenance has yielded methods of hypothetical reasoning, multiple hypothesis management, and parallel planning approaches. It is important to note that while a research program may in fact be conducted under the umbrella of a specific problem area, e.g., inherent risk analysis, nonetheless its results have application to a variety of domains. Two examples will illustrate this point.

One example of relevant research, due largely to Chandrasekaran [1985] revolves around the theory that there is a small number of information processing tasks undertaken by humans while solving problems. The richness of problem solving activity is due not to a large number of problem classes, but to both the variety of instances of a particular class of problems as well as the synthesis of two or more problem types in a complex manner. Chandrasekaran and his colleagues have identified six such generic tasks:

- Hierarchical classification,
- State abstraction,
- Knowledge-directed information passing,
- Object synthesis by design,
- Hypothesis matching, and
- Abductive assembly of explanatory hypotheses.

The implication for application is in representing, in an expert system for *any* domain, problem solving at the appropriate level of abstraction, and these generic information processing tasks serve this end. For example, object synthesis is defined as the process of designing an object (selecting and organizing components) to satisfy a set of specifications. Object is defined in a very broad sense; it can be a physical entity such as a circuit board, or software, or more abstractly, a concept such as an audit plan. Similarly, components can be wires, circuitry, subroutines, or more abstractly, concepts, actions or sub-plans.

Another area in which this research can be extended is in developing techniques that permit efficient extraction of the type of knowledge that these generic tasks entail. If knowledge elicitation methods are developed that are specific to these generic tasks, then a range of human problem solving could be efficiently elicited and represented, regardless of domain. For example, research in the psychology of problem solving has focused on the modeling of the associated cognitive processes as explicit information processes. Protocol analysis [Ericsson and Simon, 1984; Waterman and Newell, 1971] is a form of data analysis that has been used to infer underlying information processes from a person's verbal utterances while solving a problem. In thinking aloud protocols (the form of interest to most AI researchers) the subject verbally solves a problem, saying everything that is on his mind, however slight or insignificant it may seem to him. The verbalizations are transcribed and then analyzed.

There are several steps to a rigorous protocol analysis [Ericsson and Simon, 1984]:

- Create a tape of the subject verbally solving a problem.
- Transcribe the tape into segmentations of individual topics or ideas.

- Create a key-word dictionary to represent the individual thought.
- Transform the topic segments, via the dictionary, into semantic elements, consisting of knowledge elements and operator elements.
- Combine semantic elements into operator groups, each consisting of an operator and the knowledge it uses (input) and any new knowledge it creates (output).
- Create a problem behavior graph which portrays the problem solving process; arcs into nodes represent knowledge currently possessed, nodes represent operators, and arcs emanating from nodes represent newly generated knowledge.

The final output of protocol analysis, the problem behavior graph (PBG), reflects the problem solving process at the lowest level of abstraction, that of primitive concepts and operators. These primitives can be written generically so that task-related meanings for a particular domain can easily be substituted. Furthermore, *if the reasoning process is similar, the primitives for an entirely different domain may be substituted.*

Having discussed the role of AI research as establishing the technical foundation for all application development, we now turn our attention to the interaction of research and development activities. A critical issue in examining research and development is appropriate recognition of the role that each process plays in application or system creation. Both research and development in artificial intelligence are largely driven by a domain problem as depicted in Figure 2. The domain problem generates 1) *technology issues* that act as the driver of *research* activities, and 2) *requirements* that drive the *application development* process. Research activities are concerned with developing approaches, techniques, and methods that satisfy the *technology* issues of the problem, while development activities focus on the application of existing technical approaches to the system requirements. The ultimate output of the research and development process is a completed *system*. This is not to say that every problem has issues associated with it that require research before a system can be developed. In fact, most systems are built to solve problems whose technological issues have already been studied and solved with existing methods. Also, all research does not have to be driven by a specific problem. However, research is not an aimless endeavor, but rather an activity whose goal is the contribution to the advancement of a discipline. In the case of artificial intelligence that translates into technological advancements that lead to the enhanced efficacy and usefulness of computer systems that solve real-world problems.

Since the focus of research is on technological advances, results can contribute to any number of application areas. This concept is illustrated in Figure 3 and contrasts with the view presented in McCarthy et al. For example, advancements made in uncertainty propagation that result from a requirement that emerged while developing an expert system for auditing could potentially enhance the effectiveness of an expert system for portfolio management. Furthermore, systems previously developed with mature technology may benefit from ongoing research. Our perspective on research and development differs significantly from McCarthy et al.'s with respect to the

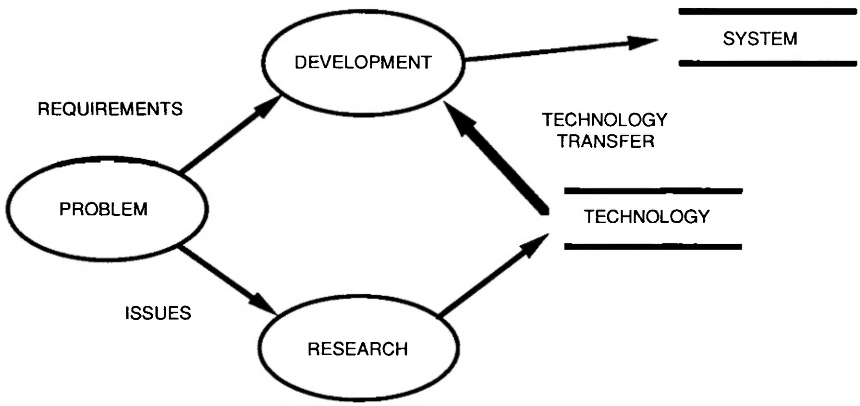

Figure 2. System Development as a Problem-Solving Process

byproducts of an application development process. McCarthy et al. appear to indicate that many expert system application development projects have an associated research component. Our experience in expert system development is in sharp contrast. Our opinion is that most expert system application developments involve *no* AI research, but rather consist of the application of *existing* AI technology. In fact, we maintain that few expert system development projects should be undertaken once critical technology gaps have been identified.

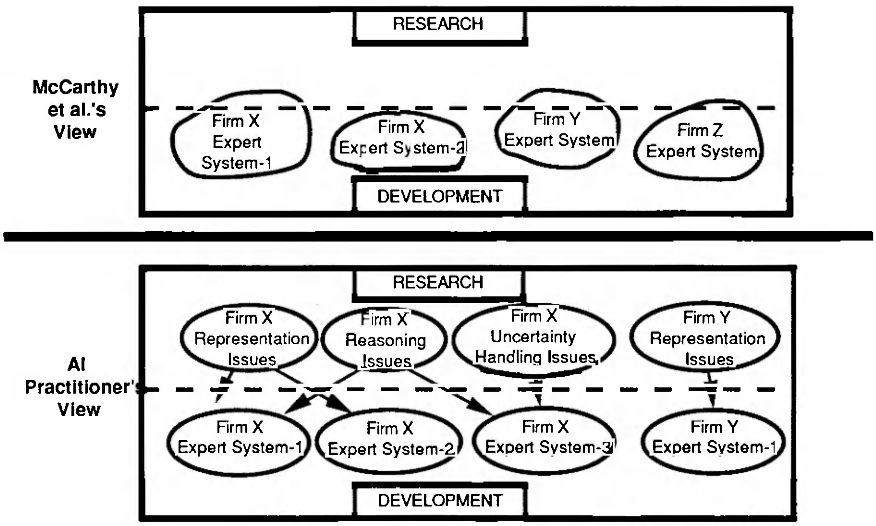

Figure 3. "Accounting Firm" System Research and Development Perspective

The process by which the technological advances are infused into the system development process is called *technology transfer* (depicted in Figure 2). This process is the single most difficult aspect of relating research to expert system development and is discussed in the next section.

3. Issues In Technology Transfer

Technology transfer, i.e., bringing research results to bear on the real-world problems of industry, remains the critical, and most difficult aspect of relating research to expert system development. There are several reasons for this difficulty. Two major ones, scalability and personnel, are addressed below.

The utility of research findings is strongly correlated to the accuracy of assessing and modeling the characteristics of the problem domain. Thus, one of the most critical issues in technology transfer is what has been termed the *scalability problem*. Waterman [1986] states "When gross simplifying assumptions are made about a complex problem, and its data, the resulting solution may not scale up to the point where it is applicable to the real problem." We have observed, on several occasions, research activities based on a domain subset that assumed away critical problem characteristics such as incomplete or conflicting data, real-time processing requirements, and needs for distributed, cooperative processing. The scalability problem involves the inability to transfer technology approaches to the often more complex, real-world problem.

Another source of difficulty with technology transfer rests with the system developers themselves. The most successful expert system development efforts are those that are undertaken by bona fide expert system developers, i.e., persons who are well-grounded in the underlying theoretical concepts of artificial intelligence and are educated in and experienced in expert system design and implementation. This foundation enables:

- Proper assessment up-front of system development feasibility.
- Knowledge of appropriate technologies to employ, e.g., what knowledge elicitation techniques would be most effective, what knowledge representation formalisms best correspond to the problem at hand.
- Appropriate system design.
- Identification of areas in which research may prove useful and in what time-frame results may be expected.
- Efficient system implementation.

In general, domain experts do not make good system developers. First, effective knowledge acquisition requires a level of abstraction that an expert is unable to achieve by virtue of his "expertness." In other words, since an expert thinks at a highly compiled level, it is difficult for him to effectively retrieve the details of his problem-solving process stored in long-term memory—a necessary step in transfering knowledge to a computer. Second, domain experts are not usually educated in both their own field and that of system design.

4. Academia And Industry Working Together

We have outlined a framework for the process of academia and industry working together. As depicted in Figure 4, in order to effectively build and field operational expert systems, it is necessary to employ both researchers and practitioners throughout the entire cycle. It is incumbent upon practitioners to remain abreast of current research which will facilitate knowledge of methods, tools, approaches, etc. that emerge. Similarly, it is necessary for the research community to keep abreast of the needs of industry in order to most effectively guide the tenor of research activity. Understanding what problems are faced by industry helps guide research towards such issues as knowledge representation, inferencing, uncertainty handling, algorithms, etc. that eventually may help solve problems faster and better. An example of this cooperation between academia and industry is given below; it is followed by an example of research in identifying the nature of expertise that has implications for future development efforts.

The problems of auditing and audit planning have been the focus of a considerable amount of research and development activity. The Peat Marwick Foundation and the Graduate School of Business of the University of Pittsburgh recently completed a 2-year research effort to develop systematic methods of risk assessment by trying to understand and model the risk assessment process within auditing [Dhar, Lewis, and Peters, 1988]. The longer range goal was to provide a foundation upon which an operational intelligent knowledge-based decision support system (expert system) to support audit planning could be designed and built.

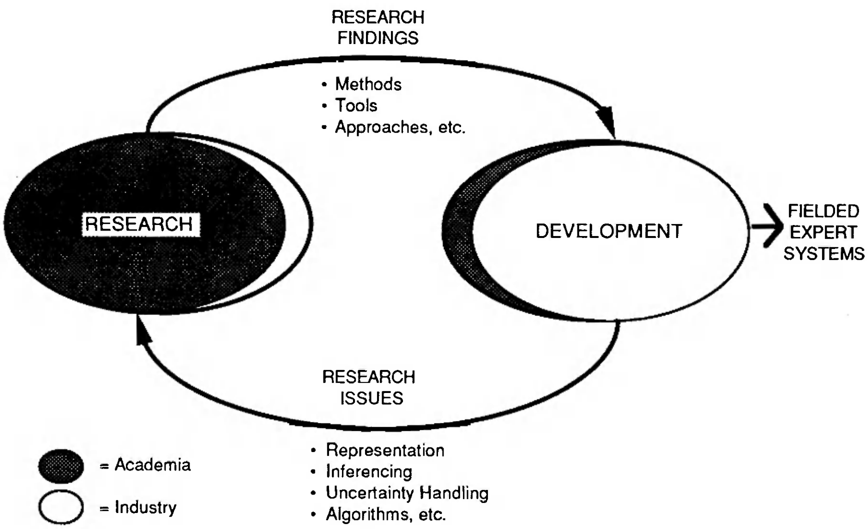

Figure 4. Academia and Industry Working Together

The results of this effort included:

- There is a difference between descriptions in the literature and what actually occurs in practice.
- Auditors do not consider it appropriate to generate numeric estimates of risk on an account-by-account basis.
- Auditors prefer to analyze a client's financial statement using knowledge about changes.

Additionally, the development of the prototype model contributed significantly to the understanding of the process of inherent risk assessment which in turn helped fine-tune the knowledge acquisition process to elicit otherwise unobtainable knowledge from the experts.

In a recent experiment, Ettenson, Shanteau, and Krogstad [1987] demonstrate that it is the way information is used, rather than the amount, that is a better indicator of expertise. In their experiment, 10 audit partners and 11 accounting seniors from 5 Big-Eight accounting firms and 11 upper-level accounting students who had completed at least one but not two formal classes in auditing and had no formal experience, were asked to evaluate accounting-related information in making judgments of materiality.

The results demonstrated that while the strategies of the students varied widely, the judgment of the professional auditor tended to reflect one primary source of information. The professionals also showed a high degree of consensus while the students did not. From an expertise standpoint, implications include:

- Simplification strategies may be an important characteristic of expert decision makers.
- Elimination of moves that are search intensive may increase performance, i.e., further research is needed in "information search" strategies of experts.
- Non-use of information by experts may reflect "skilled omission" rather than a cognitive limitation.
- Sheer amount of information is not a prerequisite to an experienced decision, rather it is the intelligent use of available information.

Implications for developmental efforts are obvious: if a better understanding of what makes an expert an "expert" is attained, then better knowledge elicitation methods can be employed, better knowledge representation schemes can be developed, and expertise can be better replicated in a computer.

5. Future of AI in Accounting

The future of AI in accounting is a bright one. While there are several examples of success in applying AI technology to develop expert systems that solve real-world problems, the field is still in its infancy. An assessment of AI activity in the Big Six accounting firms reveals that all firms are actively engaged in AI projects, ranging from strategic systems for internal use to the establishment of AI consulting groups. In addition, many universities are actively conducting AI research that has significant implications for accounting expert systems.

It is important to realize that the very nature of the fields of accounting and artificial intelligence contributes to the current and future state of accounting expert systems. Auditing is a mature discipline, with methods, approaches, and qualified experts prevalent throughout the industry. In contrast, AI continues to rapidly evolve as the result of research. Techniques and tools that are several years old are often out-of-date. A situation arises in which we are constantly applying a rapidly changing technical field, AI, to a more stable, mature discipline, e.g., auditing. Therefore, the application of AI to auditing is still very much in its infancy. The last several years have yielded more questions than answers about how best to develop auditing AI systems. Nevertheless, current research activities and application development efforts will produce the foundation for further infusion of AI into the auditing domain. The key to this foundation development is the successful integration of research and development.

Most AI research will be conducted by universities. Most operational expert systems will be implemented by industry. Understanding the relationship between research and development, the respective roles of each community, and, most important, how the two can effectively work together, will facilitate the process through which accounting AI successes will evolve.

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