# Intelligent Library Systems: Artificial Intelligence Technology and Library Automation Systems

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## 1.0 Introduction

Artificial Intelligence (AI) encompasses the following general areas of research: (1) automatic programming, (2) computer vision, (3) expert systems, (4) intelligent computer-assisted instruction, (5) natural language processing, (6) planning and decision support, (7) robotics, and (8) speech recognition.[1] Intelligent library systems utilize artificial intelligence technologies to provide knowledge-based services to library patrons and staff.

Artificial Intelligence is a broad, complex area of study, which can be difficult for non-specialists to understand. Yet, its ultimate promise is to create computer systems that rival human intelligence, and this clearly has major implications for librarianship. If we are make progress in the area of intelligent systems, we must have an well-developed understanding of AI technologies, a historical perspective on accomplishments to date, and a realistic perspective of AI as a tool with appropriate and inappropriate uses in light of current constraints. Many authors have previously provided in-depth overviews of AI technologies. The interested reader should consult either a basic[2] or a more challenging[3] introductory work for a detailed treatment of AI. There have also been several good reviews of research and development efforts relevant to librarianship.[4-9]

This paper examines certain key aspects of AI that determine its potential utility as a tool for building library systems. It discusses the barriers that inhibit the development of intelligent library systems, and it suggests possible strategies for making progress in this important area. While all of the areas of AI research indicated previously may have some eventual application in the development of library systems, this paper primarily focuses on a few that the author judges to be of most immediate significance--expert systems, intelligent computer-assisted instruction, and natural language applications. This paper does not discuss the use of AI knowledge-bases in libraries as subject-oriented library materials.

## 2.0 The Nature of Intelligence

To understand "intelligent" systems, we must first attempt to understand the nature of intelligence. Theories of human intelligence abound, but there is no consensus about what constitutes intelligence.[10] This lack of a widely accepted definition of intelligence is an obstacle for AI researchers.

Based on a review of major models of human intelligence, Cook et al. conclude that the following ten factors are most pertinent to expert system research:

1. *Acquisition*: the ability to acquire new knowledge.

2. *Automatization*: the ability to refine procedures for dealing with a novel situation into an efficient functional form.

3. *Comprehension*: the ability to know, understand, cognize and deal with novel problems.

4. *Memory management*: the ability to represent knowledge in memory, to map knowledge on to that memory representation, and to access the knowledge in memory.

5. *Metacontrol*: the ability to control various processes in intelligent behaviour.

6. *Numeric ability*: the ability to perform arithmetic operations.

7. *Reasoning*: the ability to use problem-solving knowledge.

8. *Social competence*: the ability to interact with and understand other people, machines or programs.

9. *Verbal perception*: the ability to recognize natural language.

10. *Visual perception*: the ability to recognize visual images.[11]

This is certainly a very useful list for its intended purpose; however, if we encountered a system exhibited these traits and no others, would we consider that system to be intelligent by human standards? Probably not. The reason is that our notion of human intelligence is quite likely determined by the entire gestalt of human existence--the fact that we are transient organic beings that possess five senses and feel as well as think. In short, computers lack:

> All that man is,
> All mere complexities,
> The fury and the mire of human veins.[12]

To illustrate this point, let's briefly examine one elusive feature of human intelligence: intuition. Well-known artificial intelligence critics Hubert and Stuart Dreyfus, propose a five stage model of human skill acquisition.[13] At the novice level, a learner obediently follows rules provided by an instructor, regardless of the specific situation. Based on practical experience, a learner at the advanced beginner level starts to grasp important elements in the situation that no one can teach. When the competent level is attained, the learner weighs the importance of different factors in the situation, devises goal-oriented plans, and puts those plans to work. At the proficiency level, the learner starts to make rapid, correct judgments about the solutions to particular problems without rational deliberation. At the final level, the expert relies heavily on intuition for normal problem solving activity in his or her area of expertise. Dreyfus and Dreyfus summarize:

> What should stand out is the progression *from* the analytic behavior of a detached subject, consciously decomposing his environment into recognizable elements, and following abstract rules, *to* involved skilled behavior based on an accumulation of concrete experiences and the unconscious recognition of new situations as similar to whole remembered ones.[14]

Dreyfus and Dreyfus believe that expert systems are not likely to achieve the proficiency and expert levels of skill acquisition, and, consequently, these systems should be called "competent" systems.[15]

Given the complexity of human intelligence, how soon can we expect truly intelligent computers? Moravec has the startling answer: "I believe that robots with human intelligence will be common within fifty years."[16] However, Pfaffenberger believes "the artificial intelligence technology required to create an intelligent system probably cannot be achieved using today's computers, or any possible future extension of them."[17] The question is obviously a controversial one, and, at this stage, the answer is a matter of opinion. Nonetheless, it is prudent to monitor the goals and progress of computer scientists who are attempting to develop true computer intelligence. Some of the visions of these researchers echo science fiction, and if their goals were realized they would have a major impact on human life as we know it.[18-19]

In the long-term, it may be possible to fully emulate human consciousness; however, it is currently unclear how long it will take to develop the AI tools required for this task, if these tools can be developed at all. It is also uncertain whether intelligent systems must be housed in robot bodies with advanced sensory capabilities in order to achieve human-level intelligence. If so, robotics technology will become a critical factor that either facilitates or inhibits the effort to develop truly intelligent systems.

Until major technological advances are made, we can be expect that "intelligent systems" will mimic certain key aspects of human intelligence, not replicate it. These are likely to be well-understood cognitive capabilities, although limited simulation of human emotion may occur as well to facilitate human-machine interaction. Despite the limited intelligence of these systems, they will be able to perform useful work within restricted task domains.

## 3.0 Barriers to Intelligent Systems

Although there are a few exceptions, intelligent systems are generally not in operational use today in libraries. After at least ten years of research and development, why is that we have so few production systems? Several critical problems will be discussed here.

### 3.1 General Limitations

Liebowitz identifies inadequacies in the following areas of expert system technology, leading to what he terms "artificial stupidity" in these systems: (1) common sense reasoning, (2) "deep" reasoning about the underlying principles of an area of knowledge, (3) explanation features, (4) ability to learn, (5) support for distributed expert systems, and (6) knowledge acquisition and maintenance.[20]

Yen and Tang confirm the difficulty of performing common sense reasoning in expert systems. They point to additional problems, including: (1) difficulties in allowing end-users to tailor expert systems to meet their needs, (2) high system development and maintenance costs, (3) inherent complexity of expert system development, (4) limited natural language capabilities, and (5) inability of expert systems to recognize the limits of their knowledge, deal with problems at those limits, and reject problems that exceed those limits.[21]

## 3.2 Common Sense Reasoning

Common sense is simply "general knowledge that every human being supposedly has about the world," and, consequently, common sense reasoning is the use of this knowledge to make inferences about everyday objects and events.[22] If we can build specialized medical expert systems to diagnose diseases, why is common sense reasoning about what humans view as simple problems so difficult? Sheil indicates:

> Our ordinary interactions assume a great deal of shared knowledge about an enormous variety of topics. But when we judge a task's difficulty, we tend to forget that fact and focus only on the amount of information that must be *added* to our base of common knowledge.[23]

Intelligent systems lack that common base of human knowledge, severely constraining the types of functions that they can perform. Major breakthroughs in other significant problem areas, such as natural language understanding, are likely to be dependent on progress being made in this area.

Consequently, it is significant that Lenat and his colleagues at the Microelectronics and Computer Technology Corporation are engaged in a long-term project, called Cyc, to develop a large-scale knowledge base, which would initially have enough encoded knowledge to permit a computer to understand a one-volume encyclopedia and a newspaper.[24] Work began in 1984, and, by 1994, Cyc will be given its "final exam." This will include tests of its ability to facilitate development of expert systems, English-language communication skills, knowledge acquisition abilities, and learning capabilities. It is anticipated that Cyc will be foundation upon which much more advanced intelligent systems will be constructed by AI researchers.

## 3.3 Natural Language Processing

Natural language processing systems could be utilized for a variety of purposes, including "natural language interfaces to databases and expert systems, text understanding, text generation, and machine translation."[25]

Research in natural language processing focuses on:

1. lexical/morphological analysis, which deals with words and the smallest meaningful units in language;

2. syntax, focusing on the relationship between words in larger structural units, such as sentences;

3. semantics, which deals with meaning, and

4. pragmatics, which deals with the relationship between linguistic expressions and their users.[26]

Since they require deeper levels of knowledge, semantic and pragmatic analysis are considerably more difficult than morphological and syntactic analysis. Unfortunately, semantic and pragmatic capabilities are likely to be needed to provide human-equivalent communication capabilities. Reflecting the complexity of the task of processing natural language, Smith indicates that: "Natural language systems cannot yet, and perhaps never will be able to handle truly unrestricted natural language."[27]

Discussing the technological obstacles to natural language processing, Obermeier states:

> Currently available NLP products and systems are too expensive and not user-friendly for two reasons: (1) basic research problems in understanding language and languages remain unsolved, and--somewhat as a consequence--(2) brute force algorithms prevail that have implicit limits that have been reached. . . . The underlying cause of the poor quality of NLP technology is the lack of proven theories, the unfounded support of 30-year-old formalisms that have never produced any visible results (e.g., ATN), and the ill-defined area of NLP in the first place.[28]

Natural language interfaces are utilized in database management systems; however, these systems frequently contain a limited number of highly-structured data elements.[29] The number of potential ways one would one want to retrieve these data elements is reasonably finite.

On the other hand, information retrieval systems primarily contain textual information on a wide diversity of topics, and only "quasi-natural language" interfaces, which perform restricted linguistic processing on search requests, have been successfully used with large-scale databases.[30] In general, Warner characterizes the efforts of information retrieval researchers in this area as follows:

> Traditionally, the focus has been on morphology and syntax, although semantics has recently been gaining favor. Pragmatics . . . has barely begun to be explored.[31]

Clever low-level natural language processing techniques can permit the use of free-text queries in large information retrieval systems; however, until semantic and pragmatic processing are feasible, difficult problems remain in adequately matching the true subject content of queries with that of document surrogates and documents themselves.

Since higher-level natural language processing is more tractable in restricted domains, certain task-oriented staff functions in library automation systems may be good candidates for natural language applications, but care must be taken so that staff efficiency is increased--not decreased--by this strategy (e.g., function keys may be faster than words for some tasks).

## 3.4 Knowledge Acquisition, Representation, and Maintenance

Ideally, there would be two primary ways of creating and updating knowledge bases in intelligent systems: (1) intelligent systems would distill new knowledge from full-text and other electronic information sources; and (2) human experts would add their unique insights to this knowledge base by unrestricted natural language dialogues with intelligent systems.

Unfortunately, current methods of knowledge base creation and maintenance are typically fairly tedious. Human experts must be interviewed in detail to try to record their knowledge. Knowledge must be encoded into a knowledge structure, which requires that the "knowledge engineer" have some understanding of artificial intelligence techniques to structure knowledge appropriately. Raw knowledge must be structured within a meaningful and consistent framework to be represented in the computer in a useful way. The correct knowledge representation scheme to use (e.g., rules, frames, scripts, or semantic networks) for a particular kind of knowledge is not always readily apparent. Moreover, different types of knowledge may be encoded in different knowledge representation schemes, and there must be thought given to how these different types of knowledge relate to one another and how they will function together in the overall context of the intelligent system. Once knowledge is encoded, it must be entered manually by keyboarding. The time investment to determine, represent, and enter knowledge can be significant.

Another reason for this time investment, which may not be solved by future automated techniques, is that experts cannot always articulate how they solve problems. So the knowledge engineer building a reference expert system might have a cooperative, top-notch reference librarian as his or her expert, but that individual may not be able to easily categorize different types of reference questions and explain the general strategies used to answer different types of questions. Of course, this example is in a domain where there are few formal rules, making it a worst case. Presumably, a highly-structured area like cataloging would be different; however, based on a survey of expert system applications to AACR2 cataloging, Meador and Wittig conclude: "There have been problems in every attempt to convert AACR2 into the highly structured rules necessary to run an expert system."[32] It appears that the pioneers who build intelligent library systems are likely to devote a considerable amount of effort to knowledge acquisition issues. Until improved manual and automated methods of knowledge acquisition and maintenance are devised, Brooks statement holds: "There are no short cuts as far as knowledge base development is concerned."[33]

Dreyfus and Dreyfus question whether advanced knowledge can be encoded at all:

> If one asks the experts for rules one will, in effect, force the expert to regress to the level of a beginner and state the rules he still remembers but no longer uses. If one programs them on a computer, one can use the speed and accuracy of the computer and its ability to store and access millions of facts to outdo a human beginner using the same rules. But no amount of rules and facts can capture the knowledge an expert has when he has stored his experience of the actual outcomes of tens of thousands of situations.[34]

A related problem is that many affordable expert system tools utilize simple knowledge representation structures like rules, but lack a repertoire of sophisticated structures. If the expert system tool does possess such knowledge structures, there may be a significant price to be paid in terms of system performance on affordable hardware platforms. These factors can force the development of systems in logic programming languages (e.g., Prolog) or in procedural languages (e.g., Pascal). Either one of these system development strategies can be time-consuming and complex. For example, the development of the well-known PLEXUS expert system, which is written in Pascal, took three and one-half years.[35]

## 3.5 Difficulty in Scaling Up Prototypes to Operational Systems

Intelligent systems are often created utilizing a software development methodology called prototyping:

> The objective of software prototyping is to validate a proposed design by constructing a low-cost system that has enough functionality to test out major design decisions on examples.[36]

Prototyping allows developers to fairly quickly create one or more systems that approximate the final system; however, there is no guarantee that the software techniques utilized in the small-scale prototype will work in the larger-scale production system.[37] This can lead to a false sense of accomplishment. As noted before, many library expert systems are prototypes, not production systems.

In many knowledge bases, the system developer attempts to keep individual rules independent of each other. This simplifies knowledge base maintenance and makes the knowledge base more easily extensible. Employing the knowledge base, the intelligent system uses inferencing techniques, such as forward- and backward-chaining, to approximate human reasoning. However, as a knowledge base becomes larger, it becomes more difficult to debug the logic of an essentially unstructured system:

> In point of fact, however, the sequence in which the rules is expressed takes on enormous significance, since the inference engine evaluates them in a linear, sequential fashion. . . . Moreover, for every ten rules that are entered, there are at least four times as many logical corollaries, each of which must be recognized as an outcome and specifically addressed by the insertion of a clause. . . . Furthermore, a very large expert system may break down irreparably as further expansion is attempted because its overall structure and the pattern of corollaries have grown beyond the capacity of the programming team to conceptualize them all.[38]

## 3.6 Level of Effort, Technical Expertise, and Expense

The level and calibre of effort that must be expended to create an intelligent system is directly related to the power and complexity of that system. The more "intelligent" the system is, the greater the effort that must be expended to create it and the greater the degree of expertise that is needed to do so. The need for skilled personnel combined with expensive development tools (e.g., advanced expert system shells) or techniques (e.g., original programming in logic or procedural languages) makes the creation of sophisticated intelligent systems a potentially costly venture.

Librarians and library automation vendors are already engaged in an accelerating effort to provide library patrons with access to a diversity of new computer systems.[39-40] Assuming that the needed expertise was present to create intelligent systems, what priority will libraries and vendors give to developing these systems? The reality is that staff resources, especially computer specialists, are a precious and finite commodity. It will take more staff with greater skill levels to create a complex intelligent system than a simple one, and this will inevitably affect decisions about what types of intelligent systems to build.

Unfortunately, there appears to be a limited pool of artificial intelligence expertise in the library and library automation vendor communities. Given the scope and complexity of the library automation systems that have been developed to date, there is a highly skilled body of computer professionals in these organizations; however, artificial intelligence is a specialized and somewhat esoteric area of computing that requires skills that are unlike those obtained by building conventional systems. Consequently, the likelihood is that retraining and new hiring will need to be done before any significant, widespread work is done in the area of intelligent library systems.

Information and computer scientists have been active developers of intelligent information retrieval systems.[41-48] This work has made a significant contribution to the literature, but it has produced many more prototypes than operational systems. Research will lay the theoretical foundations for the development of operational systems, but it is unlikely to produce them. That is not its purpose or intent.

Librarians have also done work in the area of library expert systems.[49-56] Some of this work appears rudimentary when compared to the work of computer and information scientists. Nonetheless, librarians have developed some exemplary systems (e.g., the PLEXUS[57] and REFSIM[58-60] systems).

What are the barriers that prevent librarians from developing sophisticated expert systems?

The type of tools librarians are likely to use (e.g., low-cost expert system shells) impose definite limits on what can be accomplished. Using these shells, it is fairly easy to create small systems with limited knowledge bases; however, some important problems require larger knowledge bases, more complex knowledge representation schemes, and greater analytic power than inexpensive expert system shells currently provide. For example, there is a considerable difference between creating an expert system that recommends 50 reference works in a single discipline and a system that recommends 1,000 reference works in all disciplines. In the first case, an inexpensive expert system shell may work well, but, in the second case, it may be totally inadequate.

The fact that many librarians have little or no training in artificial intelligence techniques is another problem. This lack of formal or informal training limits our conceptual horizons, and it reduces the repertoire of technological tools that we can skillfully deploy to create intelligent systems. Hopefully, library schools will provide more in-depth training to new generations of librarians.

Since library staff are rarely devoted full-time to building expert systems and hardware and software budgets are frequently tight, resource constraints also impose limits on the types of systems that librarians can create.

Finally, risk aversion is a problem. When library administrators invest scarce resources in innovative projects, they usually expect success, preferably rapid success. Unfortunately, the closer to the cutting edge a project is, the greater the chance that it will fail to produce a fully functional system. Playing it safe often leads to systems designed for "success," not sophisticated functionality. At this stage in the evolution of library expert systems, more calculated risk taking is needed in system development efforts.

Given these problems, where will future intelligent library systems come from? In the late 1960's and early 1970's, a few libraries developed single-function or integrated online systems. Some of these systems became quite important latter to the library community as a whole because they were successfully marketed by library automation vendors as turnkey systems. Vendors also created their own turnkey library systems. Today, few libraries develop their own integrated library system; most buy a turnkey system from a vendor. This is a major reason why integrated systems are so prevalent today--each library does not have to build its own system. As long as we are in an era of hand-crafted intelligent systems, libraries will make limited use of these systems. We need turnkey intelligent systems, which can be modified for local use. As in the past, the source of these systems may be mixed, with both vendors and a few exceptional libraries producing systems that vendors can successfully market. However, there must be significant market demand for these systems, appropriate artificial intelligence tools to build them with, and skilled staff to develop them.

Vendors are beginning to show some interest in intelligent systems. As a spin-off of the PLEXUS project, Tome Associates has developed TOME SEARCHER, an intelligent front-end to commercial computer science, electrical engineering, and information technology databases.[61] Other vendors have initiated research projects or developed operational systems that incorporate some aspects of artificial intelligence technology.[62-65]

## 4.0 Strategies for Future Progress

By recognizing the limitations of contemporary artificial intelligence techniques, we can establish realistic goals for intelligent library systems and devise appropriate system development strategies. This section discusses some promising approaches to the application of artificial intelligence techniques in library automation systems.

### 4.1 Targeted Development Efforts

Artificial intelligence is a means to an end. Like any tool, it has strengths and limitations. Our true goal is not to create systems based on artificial intelligence technologies--it is to create the most powerful, flexible, and easy-to-use systems possible for our ourselves and our patrons. AI is one tool in the toolbox, which should be employed when the characteristics of the task at hand indicate that an AI solution that is called for.

Some of our goals may not be well suited for AI techniques or they may require a judicious, limited application of AI technology. For example, Brooks has expressed pessimism about the appropriateness of AI as a tool to build information retrieval systems:

> For several reasons, IR does not seem to be an ideal problem domain for an expert system application. It is a domain that is neither well bounded nor narrow nor homogeneous. In some retrieval environments and for some aspects of the retrieval process, there may be no obvious human experts, and what experts there are often do not agree. . . . Further, although little research has been conducted in the kinds of knowledge required by the knowledge base of an intelligent IR system, all the indications are that the knowledge needed would be extensive and wide-ranging and would include knowledge of the subject domain of the queries and documents being processed.[66]

One response to the stated problems is to abandon efforts to create intelligent retrieval systems; however, another approach is to try to overcome the inherent difficulties by restricting the goals and domain of the system. For example, the CANSEARCH system builds on the knowledge inherent in MeSH subject headings to provide assistance to researchers searching MEDLINE for cancer information.[67] CANSEARCH is not a global solution to the problem of providing intelligent information retrieval, but it effectively addresses one specialized need.

We need to carefully analyze complex problem areas looking for aspects of these areas that are amenable to the application of AI techniques. For example, providing the user with intelligent assistance in selecting an appropriate database from a wide variety of remote and locally-mounted databases may be an easier task than helping the user to devise optimal search strategies for each of those databases. By use of a mix of AI and conventional programming techniques, we may be able to build powerful systems that solve many, but not all, of the problems associated with a domain like information retrieval.

Moreover, we need to actively identify domains that are inherently well-bounded, but are complex enough to truly require AI techniques. It may be that certain aspects of acquisitions, cataloging, circulation, interlibrary loan, preservation, and serials are fertile ground for the selective application of AI techniques. However, aside from cataloging, little effort has been made to create intelligent systems in these areas. Attempts to create expert cataloging systems have generally run aground because of the ambiguities inherent in interpreting AACR2; however, further revisions of the code could specifically address these ambiguities with the aim of facilitating the creation of intelligent cataloging systems.[68]

## 4.2 Machine Intelligence vs. Machine-Aided Intelligence

One important determinant of the complexity and feasibility of intelligent systems is the locus of control in the system. Smith contrasts machine intelligence with machine-aided intelligence:

> Where machine intelligence dominates, an effort is made to keep as much control as possible within the computer by automating decision-making and execution of tasks. Where machine-aided intelligence dominates, the user is in control with the computer providing suggestions and gathering information to aid the user's decision-making.[69]

Given current constraints, machine intelligence systems will be very difficult--if not impossible--to create for large, complicated domains where levels of performance approaching human intelligence are required. It is likely that the ambitions of machine intelligence systems must be much more modest, restricting the usefulness of AI techniques to a smaller set of applications than would otherwise be the case. However, by focusing on how AI can be used to augment--not replace--humans, a much wider range of applications can be fruitfully considered.

It is possible to conceive of a variety of AI-based tools that would assist users in performing various tasks. For example, the prototype DANEX system guides researchers in performing certain types of statistical data analysis.[70] A variety of prototype "intelligent agent" systems have been created to perform restricted, repetitive tasks for users, such as compiling monthly reports.[71]

## 4.3 Technological Convergence and Synergy

We are in a period of swift technological change that is characterized by the regular emergence of promising new computer technologies, the continuing dramatic improvement of the price/performance of existing technologies, and the blending of previously discrete technologies to form powerful new hybrids.

Parsaye et al. indicate that the convergence of several major technologies has created "intelligent databases":

> Intelligent databases represent the evolution and merger of several technologies, including automatic discovery, hypermedia, object orientation, expert systems, and traditional databases.[72]

The synergistic interplay of these technological tools opens up new horizons for the creation of intelligent library systems. In their thought-provoking book Intelligent Databases: Object-Oriented, Deductive Hypermedia Technologies, Parsaye et al. explore the architecture of intelligent database systems in detail.[73]

Based on an extensive, insightful review of subject searching techniques in online catalogs, Hildreth identifies a variety of strategies for improving future online catalogs and other information retrieval systems:

> To summarize, these include natural language query processing; direct or indirect mapping/linking of free text terms to terms in the controlled vocabulary used to index documents; flexible, heuristic retrieval strategies; but, primarily, probabilistic retrieval with weighted-term, combinatorial searching and the ranking of output; and "user-engaged" relevance feedback procedures for automatic query expansion and modified search strategies.[74]

It is possible that the use of these innovative techniques combined with the judicious use of AI techniques could solve the more tractable parts of the overall information retrieval problem, resulting in more powerful and useful systems.

The shape of future library systems cannot be known today--the components of these systems and their arrangement will change over time in ways that we cannot foresee. However, it appears that we have much to gain--and little to lose--by exploring how conventional data processing, AI, and other emerging technologies could work together to complement each other in a synergistic fashion. We should not approach AI as purists, but rather as pragmatists.

## 4.4 Promising AI Tools and Techniques

Given the breadth and diversity of AI, there are a number of technological tools and techniques that may be valuable in constructing intelligent library systems. Some, such as neural networks,[75] are too immature to assess their usefulness. The following list briefly summarizes selected AI tools and techniques that I currently feel hold special promise. It is by no means a comprehensive list of potentially useful tools and techniques.

1. Blackboard and Cooperative Distributed Problem Solving Systems

We have previously discussed the problems of knowledge base structure and size. Blackboard architectures partition knowledge into separate knowledge sources that exchange information via a common data area, called a blackboard.[76] These knowledge sources specialize in particular aspects of the problem to be solved. Under the control of a scheduling component, knowledge sources take turns working on specific aspects of a problem, and, in incremental steps, the problem is solved by their collective effort. Cooperative distributed problem solving systems work in a similar fashion; however, each knowledge source is capable of more independent problem solving within its area of expertise, and it has more advanced communication and control capabilities.[77] A metaphor is that knowledge sources in blackboard systems are like parts of the brain, while in cooperative distributed problem solving systems they are like human members of a team.[78]

2. Frames

Typically, a frame represents a particular person, object, or event in the world. Since we normally view these things as occurring in groups with common stereotyped characteristics (e.g., patrons), frames are usually grouped in classes, with the frames in a particular class having a common structure. Each characteristic of the thing described by the frame is represented by a slot. Each slot normally contains a value, and this can be a default value. In addition to containing values, slots can contain procedural attachments, executable procedures that are invoked under specified circumstances. Frames of a particular class can be organized into a hierarchy, with lower-level frames inheriting the characteristics of their antecedents. Frames are particularly well suited to representing knowledge in intelligent library systems. For example, consider how easily a subject heading scheme like MeSH could be represented in a frame structure. For further information on frames, see Parsaye and Chignell[79] and Walters and Nielsen.[80]

3. User Models

A user model is simply a representation of an individual user or a class of users in an intelligent system. The system utilizes the knowledge contained in the user model to tailor its interactions to fit the specific needs of the user or class of users. There are numerous possible dimensions of user models, including: (1) class of users vs. individual user, (2) explicit description of the user by the system designer (or the user) vs. implicit deduction of the user's characteristics by the system, (3) short-term vs. long-term user characteristics, and (4) dynamic vs. static user characteristics.[81] Norcio and Stanley view user models as one of four knowledge base components of "adaptive human-computer interfaces," with the other components being interaction, task/domain, and system knowledge.[82] By creating intelligent library systems that employ user models and other adaptive human-computer interface components, developers can create systems that have more sophisticated interaction and knowledge-processing capabilities.

4. Intelligent Computer-Assisted Instruction

Intelligent Computer-Assisted Instruction (ICAI) systems can provide users with both education and training. Rickel indicates that CAI, the last generation of computer-based instruction tools, "requires teachers to fully specify presentation text, all questions and their associated answers, and a strict flow of control through the course, allowing at best different branches to be taken based on the students preenumerated possible responses."[83] By contrast, ICAI systems can provide truly individualized instruction that is tailored to meet the user's specific needs.[84] An ICAI system can contain domain, pedagogical, and user knowledge. Utilizing this knowledge, the system can identify the user's learning needs, diagnose the user's learning problems, and present appropriate instructional material. As the number of systems we utilize increases, the need to provide on-demand education and training to local and remote users also increases. ICAI can potentially address this need.

Given the current capabilities of affordable products in the AI marketplace, the implementation of systems utilizing blackboard, cooperative distributed problem solving, and ICAI techniques may require original programming. Fortunately, AI tools are becoming more powerful and cheaper as time goes on, and we can expect that less original programming will be needed in the future to provide sophisticated capabilities.

## 5.0 Conclusion

Through the application of artificial intelligence technologies, numerous prototype intelligent library systems have been created for cataloging, indexing, information retrieval, reference, and other purposes; however, relatively few of these systems have evolved into production systems that are used in the day-to-day operations of libraries. Fox reminds us that: "While AI research has been underway for more than three decades, it is only in the past six years that AI's impact has been measurable."[85] To some degree, the lack of penetration of AI technologies in libraries is due to the fact that appropriate tools and techniques have only been widely available for a relatively short time. However, there were other theoretical, technological, fiscal, and human resource barriers as well, and these significant problems are ongoing.

This paper has outlined some of the major limitations of selected AI technologies of particular interest to libraries and suggested some possible strategies for making progress in building intelligent library systems. It is critical that we seek the middle ground between the view that AI will revolutionize libraries in the foreseeable future and the view that it will have little or no effect. AI offers us a powerful set of tools, especially when they are combined with conventional and other innovative computing tools. However, it will not be an easy task to master those tools and employ them skillfully to build truly significant intelligent systems. Libraries and vendors who have ambitious system development goals are likely to need to invest substantial resources in achieving those ambitions. The use of intelligent library systems is unlikely to be widespread until we move from the current era of hand-crafted intelligent systems to a future era of turnkey intelligent systems. To accomplish this goal, vendors and a small number of progressive libraries will need to create powerful, transportable, and marketable intelligent library systems, based on the continuing advances made in the commercial AI marketplace.

References

1. Henry C. Mishkoff (revised by Dan Shafer and Daniel W. Rasmus), Understanding Artificial Intelligence, 2nd ed. (Indianapolis: Howard W. Sams & Company, 1988).

2. Louis E. Frenzel, Jr., Crash Course in Artificial Intelligence and Expert Systems (Indianapolis: Howard W. Sams & Co., 1987).

3. George F. Luger and William A. Stubblefield, Artificial Intelligence and the Design of Expert Systems (Redwood City, CA: Benjamin/Cummings Publishing Co., 1989).

4. Ralph Alberico and Mary Micco, Expert Systems for Reference and Information Retrieval (Westport, CT: Meckler, 1990).

5. Rao Aluri and Donald E. Riggs, "Application of Expert Systems to Libraries," Advances in Library Automation and Networking 2 (1988): 1-43.

6. P. F. Anderson, "Expert Systems, Expertise, and the Library and Information Professions," Library and Information Science Research 10 (October 1988): 367-388.

7. Joseph M. A. Cavanagh, "Library Applications of Knowledge-Based Systems," The Reference Librarian no. 23 (1989): 1-19.

8. Tim Holthoff, "Expert Librarian Applications of Expert Systems to Library Technical Services," Technical Services Quarterly 7, no. 1 (1989): 1-16.

9. Linda C. Smith, "Artificial Intelligence and Information Retrieval," Annual Review of Information Science and Technology 22 (1987): 41-77.

10. Robert J. Sternberg, "Intelligence," in The Oxford Companion to the Mind, ed. Richard L. Gregory and O. L. Zangwill (Oxford: Oxford University Press, 1987), 375-379.

11. John Cook, A. Dale Whittaker, Ronald H. Thieme, Owen R. Smith, and Gavriel Salvendy, "Human Intelligence Models and Their Implications for Expert System Structure and Research," Behaviour and Information Technology 7 (October-December 1988): 424-425.

12. Yeats, William Butler, "Byzantium," in The Collected Poems of W. B. Yeats (London: Macmillan, 1967), 280.

13. Hubert L. Dreyfus and Stuart E. Dreyfus (with Tom Athanasiou), Mind Over Machine: The Power of Human Intuition and Expertise in the Era of the Computer (New York: The Free Press, 1986), 21-36.

14. Ibid, 35.

15. Ibid, 102-103.

16. Hans Moravec, Mind Children: The Future of Robot and Human Intelligence (Cambridge: Harvard University Press, 1988), 6.

17. Bryan Pfaffenberger, Democratizing Information: Online Databases and the Rise of End-User Searching (Boston: G. K. Hall & Co., 1990), 175.

18. Hans Moravec, Mind Children.

19. Grant Fjermedal, The Tomorrow Makers: A Brave New World of Living-Brain Machines (New York: Macmillan, 1986).

20. Jay Liebowitz, "How Much 'Artificial Stupidity' Do Expert Systems Possess?," Information Age 11 (October 1989): 225-228.

21. Chi-Chung Yen and Hung-Lian Tang, "Inside an Expert System: Strengths, Weaknesses, and Trends," The Journal of Computer Information Systems 30 (Fall 1989): 36-37.

22. Colin Beardon, Artificial Intelligence Terminology: A Reference Guide (Chichester, England: Ellis Horwood Limited, 1989), 43.

23. Beau Sheil, "Thinking About Artificial Intelligence," Harvard Business Review 65 (July-August 1987): 93.

24. Douglas B. Lenat and R. V. Guha, Building Large Knowledge-Based Systems: Representation and Inference in the Cyc Project (Reading, MA: Addison-Wesley Publishing Company, 1990), 28-30, 356-358. (Irene L. Travis identified potential problem areas within the Cyc project in an insightful paper given at the 27th Annual Clinic on Library Applications of Data Processing at the University of Illinois at Urbana-Champaign.)

25. Amy J. Warner, "Natural Language Processing," Annual Review of Information Science and Technology 22 (1987): 79.

26. Tamas E. Doszkocs and Bella Hass Weinberg, "Natural Language Interfaces for Information Retrieval," in Gateway Software and Natural Language Interfaces: Options for Online Searching, ed. James A. Benson and Bella Hass Weinberg (Ann Arbor, MI: Pierian Press, 1988): 127.

27. Linda C. Smith, "Knowledge-Based Systems, Artificial Intelligence and Human Factors," in Information Technology and Information Use: Towards a Unified View of Information and Information Technology, ed. Peter Ingwersen, Leif Kajberg, and Annelise Mark Pejtersen (London: Taylor Graham, 1986), 101.

28. Klaus K. Obermeier, Natural Language Processing Technologies in Artificial Intelligence: The Science and Industry Perspective (Chichester, England: Ellis Horwood Limited, 1989), 192.

29. Tamas E. Doszkocs and Bella Hass Weinberg, "Natural Language Interfaces for Information Retrieval," 128-129.

30. Ibid, 129-131.

31. Amy J. Warner, "Artificial Intelligence and the User Interface," Bulletin of the American Society for Information Science 15 (April/May 1989), 18.

32. Roy Meador III and Glenn R. Wittig, "Expert Systems for Automatic Cataloging Based on AACR2: A Survey of Research," Information Technology and Libraries 7 (June 1988): 170.

33. Helen M. Brooks, "Information Retrieval and Expert Systems--Approaches and Methods of Development," in Intelligent Information Retrieval: Informatics 7, ed. Kevin P. Jones (London: Aslib, 1983), 71.

34. Hubert L. Dreyfus and Stuart E. Dreyfus, Mind Over Machine, 108.

35. A. Vickery, "The Experience of Building Expert Search Systems," in Online Information 88: 12th International Online Information Meeting, vol. 1 (Oxford: Learned Information, 1988), 312.

36. Michael Lowry and Raul Duran, "Knowledge-Based Software Engineering," in The Handbook of Artificial Intelligence, vol. 4, ed. Avron Barr, Paul R. Cohen, and Edward A. Feigenbaum (Reading, MA: Addison-Wesley Publishing Company, 1989), 262.

37. Mark S. Fox, "AI and Expert System Myths, Legends, and Facts," IEEE Expert 5 (February 1990): 16.

38. Bryan Pfaffenberger, Democratizing Information, 154-55.

39. Charles W. Bailey, Jr., "Public-Access Computer Systems: The Next Generation of Library Automation Systems," Information Technology and Libraries 8 (June 1989): 178-185.

40. Charles W. Bailey, Jr., "Integrated Public-Access Computer Systems: The Heart of the Electronic University," Advances in Library Automation and Networking 3 (1989): 1-33.

41. Giorgio Brajnik, Giovanni Guida, and Carlo Tasso, "IR-NLI II: Applying Man-Machine Interaction and Artificial Intelligence Concepts to Information Retrieval," in ACM SIGIR 11th International Conference on Research and Development in Information Retrieval (New York: The Association for Computing Machinery, 1988), 387-399.

42. W. B. Croft and R. H. Thompson, "$I^3R$: A New Approach to the Design of Document Retrieval Systems," Journal of the American Society for Information Science 38 (November 1987): 389-404.

43. Susan Gauch and John B. Smith, "An Expert System for Searching in Full-Text," Information Processing and Management 25, no. 3 (1989): 253-263.

44. Richard S. Marcus, "Expert Retrieval Assistance Development and Experimentation," in ASIS '88: Proceedings of the 51st ASIS Annual Meeting, ed. Christine L. Borgman and Edward Y. H. Pai (Medford, NJ: Learned Information, Inc., 1988), 115-119.

45. Ira Monarch and Jaime Carbonell, "CoalSORT: A Knowledge-Based Interface," IEEE Expert 2 (Spring 1987): 39-53.

46. Steven Pollitt, "CANSEARCH: An Expert Systems Approach to Document Retrieval," Information Processing & Management 23, no. 2 (1987): 119-138.

47. Lisa F. Rau, "Knowledge Organization and Access in a Conceptual Information System," Information Processing & Management 23, no. 4 (1987): 269-283.

48. Peretz Shoval, "Principles, Procedures and Rules in an Expert System for Information Retrieval," Information Processing & Management 21, no. 3 (1985): 475-487.

49. Charles W. Bailey, Jr., Jeff Fadell, Judy E. Myers, and Thomas C. Wilson, "The Index Expert System: A Knowledge-Based System to Assist Users in Index Selection," Reference Services Review 17, no. 4 (1989): 19-28.

50. Nancy J. Butkovich, Kathryn L. Taylor, Sharon H. Dent, and Ann S. Moore, "An Expert System at the Reference Desk: Impressions from Users," The Reference Librarian no. 23 (1989): 61-74.

51. Robert Carande, "INDEXES: A Micro-Based Expert System," Small Computers in Libraries 8 (December 1988): 26-27.

52. Roy Davies and Brian James, "Towards an Expert System for Cataloguing: Some Experiments Based on AACR2," Program 18 (October 1984): 283-297.

53. Deborah Hanfman, "AquaRef: An Expert Advisory System for Reference Support," The Reference Librarian no. 23 (1989): 113-133.

54. Susanne M. Humphrey, "MedIndEx System: Medical Indexing Expert System," Information Processing & Management 25, no. 1 (1989): 73-88.

55. Karen F. Smith, "POINTER vs. Using Government Publications: Where's the Advantage?," The Reference Librarian no. 23 (1989): 191-205.

56. Samuel T. Waters, "Answerman, the Expert Information Specialist: An Expert System for Retrieval of Information from Library Reference Books," Information Technology and Libraries 5 (September 1986): 204-212.

57. A. Vickery and H. M. Brooks, "PLEXUS--The Expert System for Referral," Information Processing and Management 23, no. 2 (1987): 99-117.

58. James R. Parrott, "REFSIM: A Bimodal Knowledge-Based Reference Training and Consultation System," Reference Services Review 16, no. 1-2 (1988): 61-68.

59. James R. Parrott, "Simulation of the Reference Process," The Reference Librarian no. 21 (1988): 189-207.

60. James R. Parrott, "Simulation of the Reference Process, Part II: REFSIM, an Implementation with Expert System and ICAI Modes," The Reference Librarian no.23 (1989): 153-176.

61. A. Vickery, "The Experience of Building Expert Search Systems," 302.

62. Robert H. Ledwith, "Development of a Large, Concept-Oriented Database for Information Retrieval," in ACM SIGIR 11th International Conference on Research & Development in Information Retrieval (New York: The Association for Computing Machinery, 1988), 651-661.

63. "VTLS Offers Intelligent Front End, Expert System Package to New VTLS-89 Software," Library Hi Tech News (September 1989): 15-16.

64. Stuart Weibel, Michael Oskins, and Diane Vizine-Goetz, "Automated Title Page Cataloging: A Feasibility Study," Information Processing & Management 25, no. 2 (1989): 187-203.

65. Stephen A. Weyer, "Questing for the 'DAO': DowQuest and Intelligent Text Retrieval," Online 13 (September 1989): 39-48.

66. H. M. Brooks, "Expert Systems and Intelligent Information Retrieval," Information Processing & Management 23, no. 4 (1987): 378.

67. Steven Pollitt, "CANSEARCH: An Expert Systems Approach to Document Retrieval," 121-137.

68. Roy Davies and Brian James, "Towards an Expert System for Cataloguing: Some Experiments Based on AACR2," 296.

69. Linda C. Smith, "Machine Intelligence vs. Machine-Aided Intelligence as a Basis for Interface Design," in Proceedings of the Second Conference on Computer Interfaces and Intermediaries for Information Retrieval (Alexandria, VA: Office of Information Systems and Technology, Defense Technical Information Center, 1986), 107.

70. I. Bockenholt, M. Both, and W. Gaul, "A Knowledge-Based System for Supporting Data Analysis Problems," Decision Support Systems 5, no. 4 (1989): 345-354.

71. Charles W. Bailey, Jr., "Intelligent Multimedia Computer Systems: Emerging Information Resources in the Network Environment," Library High Tech 8, no. 1 (1990), 29-41.

72. Kamran Parsaye, Mark Chignell, Setrag Khoshafian, and Harry Wong, "Intelligent Databases," AI Expert (March 1990): 38.

73. Kamran Parsaye, Mark Chignell, Setrag Khoshafian, and Harry Wong, Intelligent Databases: Object-Oriented, Deductive Hypermedia Technologies (New York: John Wiley & Sons, 1989).

74. Charles R. Hildreth, Intelligent Interfaces and Retrieval Methods for Subject Searching in Bibliographic Retrieval Systems (Washington, D.C.: Cataloging Distribution Service, Library of Congress, 1989): 106.

75. William F. Allman, Apprentices of Wonder: Inside the Neural Network Revolution (New York: Bantam Books, 1989).

76. H. Penny Nii, "Blackboard Systems," in The Handbook of Artificial Intelligence, vol. 4, ed. Avron Barr, Paul R. Cohen, and Edward A. Feigenbaum (Reading, MA: Addison-Wesley Publishing Company, 1989), 1-82.

77. Edmund H. Durfee, Victor R. Lesser, and Daniel D. Corkill, "Cooperative Distributed Problem Solving," in The Handbook of Artificial Intelligence, vol. 4, ed. Avron Barr, Paul R. Cohen, and Edward A. Feigenbaum (Reading, MA: Addison-Wesley Publishing

Company, 1989), 83-147.

78. Ibid, 93-94.

79. Kamran Parsaye and Mark Chignell, <u>Expert Systems for Experts</u> (New York: John Wiley & Sons, 1988), 161-210.

80. John R. Walters and Norman R. Nielsen, <u>Crafting Knowledge-Based Systems: Expert Systems Made Easy/Realistic</u> (New York: John Wiley & Sons, 1988), 209-252.

81. P. J. Daniels, "Cognitive Models in Information Retrieval--An Evaluative Review," <u>Journal of Documentation</u> 42 (December 1986): 275-278.

82. Anthony F. Norcio and Jaki Stanley, "Adaptive Human-Computer Interfaces: A Literature Survey and Perspective," <u>IEEE Transactions on Systems, Man, and Cybernetics</u> 19 (March/April 1989): 401-407.

83. Jeff W. Rickel, "Intelligent Computer-Aided Instruction: A Survey Organized Around System Components," <u>IEEE Transactions on Systems, Man, Cybernetics</u> 19 (January/February 1989), 40.

84. Ibid, 40-57.

85. Mark S. Fox, "AI and Expert System Myths, Legends, and Facts," 8.