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A METHODOLOGY FOR CLASSIFYING THE COMPLEXITY OF EXPERT SYSTEMS: A PILOT STUDY

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ABSTRACT

The focus of this paper is to present a classification methodology for evaluating the complexity of expert systems. Complexity in the area of expert systems consists of two basic dimensions: the complexity of the underlying knowledge residing with the experts and the complexity of the technology incorporated into a given system. The classification methodology was developed and tested for its ability to accurately differentiate expert systems with a pilot sample of six expert systems. Using this approach provides a basis for managers to assess the complexity of a particular expert system and thereby assist in planning the scope of the development and implementation effort and the "fit" of a particular project with the firm's internal resources and the needs of its competitive environment.

1. INTRODUCTION

Expert systems have matured to the point where the key challenge facing management is no longer access to the technology. Expert systems development tools have reached the stage where higher level shells, written in broadly available programming languages for a wide range of general purpose computers, have come to dominate more exotic tools designed for special purpose machines.

Having access to an enabling technology, however, by no means guarantees that the technology will be successfully applied. Industry's experience with expert systems technology truly underscores this point. The missing link between having access to generic technology and successfully applying it to solve real problems in business is a management problem. Managers are still widely uncomfortable with expert systems technology and largely decline to participate in line-oriented projects that use it. Without their participation, it is difficult to pick the right problems to solve, to insure appropriate staffing and management of development efforts, to create appropriate user interfaces, and to insure that the system will evolve suitably over time.

2. A METHODOLOGY FOR CLASSIFYING EXPERT SYSTEM PROJECTS

The focus of this paper is to provide a conceptual foundation to place either a current or proposed expert system in a business perspective. We define expert systems as those computer-based systems that go beyond organizing and retrieving information to embody human reasoning and expertise that operates on information to either perform or assist in the performance of specific decision-making (Harmon, Maus and Morrissey 1988). Throughout 1988, a research project was conducted with a consortium of large corporations to address the management problems associated with the development and delivery of such systems.

The managers and developers in our research consortium collectively agreed that expert systems have fundamental differences with traditional information processing applications and, thus, that new management frameworks to guide expert systems development could have substantial value. It was felt that there was an absence of methodologies to guide the development of and monitor the ongoing evolution of expert systems.

It made sense that no single solution set in terms of project staffing, technology, and knowledge engineering processes existed for all types of expert systems. Thus, as a first step, the creation and validation of a classification methodology that focused on problem complexity and technology complexity to distinguish between different expert systems was required. Only then could situation-specific development strategies be generated. Clancy (1985) previously conducted research on expert systems based on the same approach.

The primary objective of the classification framework described here is to accurately characterize the relative complexity of a given system or, more broadly, of a given application of computer technology. The degree of system complexity was seen by industry participants as the critical factor affecting staffing, budget, technical issues and the overall management process. Complexity in the area of expert systems consists of two basic dimensions. The first dimension is the complexity of the underlying "knowledge" residing with the experts. Thus, the experts and decision processes behind the expert system itself were studied. Knowledge complexity was measured using research variables relating to the given decision-making process, the depth and breadth of the knowledge base of the experts, and the information inputs required by experts in making decisions.

The second dimension of the framework focused on the complexity of the technology incorporated into a given system. Technological complexity was assessed using research variables that focused on hardware platforms employed, the scope of the programming effort required for both the knowledge bases and the databases used in the system, development technologies, and factors pertaining to systems integration.

3. THE PILOT STUDY SAMPLE

The classification methodology was developed and tested for its ability to accurately differentiate expert systems with a pilot sample of six expert systems. It should be noted that all of these systems were identified as successes within their organizations, which was deemed appropriate because the purpose of the research effort at this point in time was classification according to complexity and not success versus failure diagnosis. These expert systems are summarized for the reader's convenience below and will be used in subsequent discussion to illustrate the research variables within the methodology.

THE LIFE UNDERWRITER: An underwriting system for life insurance applications, created by a leading reinsurance organization. The project has been a classic case of intrapraneurship within an established organization. Operational on both PC and mainframe environments, this system combines medical, underwriting, and actuarial knowledge in a highly complex system, one which is currently being marketed across the insurance industry. New life insurance applications are submitted to the expert system, which screens out immediate "accepts" and "declines" based medical, financial, and avocational risk factors. The remaining cases are resolved through interactive consultation that draws on extensive medical knowledge bases. The system is also being integrated with mainframe administrative systems for sharing of data and for the pricing of underwritten cases based on specific insurance products.

XCON: An expert system that verifies computer configurations for all products ordered within a large computer manufacturer. This system is an integral part of the company's manufacturing and delivery processes, since all products shipped are customized to users's requirements. All new orders from the sales force are passed through this expert system, which checks compatibility between ordered components and generates installation and testing procedures. Its database of computer components is massive and is drawn from many different parts of the organization such as manufacturing, product engineering, product marketing, and sales. The "rules" for configuration are constantly changing as the company introduces new computer products and components. The sheer size and complexity of this knowledge base has led management to explore new methods for acquiring knowledge and encoding it into the system.

FX TRADER: Developed by a commercial bank, this system assists in the process of auditing all foreign exchange transactions made by the bank. Here again, part of the system is "batch" and part is "interactive." All transactions are first automatically scanned for statistical outliers in terms of price spreads. Individual transactions identified in this fashion are presented to auditors for interactive investigation. An excellent graphics user interface aids the user in this consultation. It was built as a standalone system, using a LISP-based tool for a special purpose AI computer. Management is now exploring a new generation of development tools geared for general purpose graphics workstations.

REVA: A system that assists in the diagnosis of mechanical problems in rotating equipment often found in manufacturing plants through vibration analysis theory. It is a consultation system that prompts the user for specific diagnostic information and inferences through a relatively complex decision tree to suggest the causes for observed problems. Another case of intrapraneurship, REVA was developed by a newly formed group within a leading engineering services company. The group calls upon engineering experts in other parts of the company for assistance on client-driven expert system projects.

TELEX ROUTER: Developed by another commercial bank, an expert system that receives all telexes coming into the bank's headquarters, reformats them, and routes them to individual employees. Money transfers are separated from other messages. The system operates in a batch production mode, drawing on the company's standard employee address databases. The levels of technical integration with existing computer and telecommunications systems is high.

CLINT: Developed by the real estate department of a large insurance company, an expert system that identifies the often complex legal requirements necessary for closing specific real estate transactions. Loan officers use this standalone PC system regularly to prepare for closings. Management has noted that the consistency of problem identification provided this system has improved the quality and speed of this work. It is another consultation-type system.

4. DEFINING KNOWLEDGE COMPLEXITY

The knowledge dimension of the classification framework assesses the complexity of the underlying decision process or problem-solving within the expert system. We hypothesized that this dimension consists of three basic factors:

- The characteristics of the domain or underlying field of knowledge being automated
- The characteristics of the information inputs employed by experts to make decisions
- The characteristics of the decision process itself

More specific research variables were then defined within each of these areas and are described below in detail.

4.1 Domain Characteristics

Breadth/Scope of the Domain(s). The role of experts and knowledge engineers in the development process has been noted by many sources (Harmon, Maus and Morrissey 1988; Hart 1986). By examining the domain content of a specific expert system with both sets of individuals on a given project, the number of specific domains or distinct fields of expertise modelled into the system could be identified. The authors differentiated between systems with a) a single domain, b) two domains, and c) three or more domains. For example, REVA, the expert system that diagnoses equipment failures for plant machinery, embodies the single domain of vibration analysis, whereas LIFE UNDERWRITER, the system to underwrite life insurance applications, requires the separate fields of medical science, underwriting, actuarial science, and financial analysis.

Depth of Domain(s). To assess the level or depth of specialization of the domain(s) embodied in the expert system, we examined the education and work experience of the experts who contributed knowledge to the system. Much has been written about the characteristics of experts, their methods of acquiring skill, and their application of that skill to problem solving (Newell and Simon 1972; Schank and Childers 1984). Dreyfus and Dreyfus (1986) provide an excellent discussion of the difference between intuitive reasoning and analytical methods in expert decision-making. For the present research, the authors relied on surrogate measures to indicate the depth of the domains incorporated into the expert systems. We tracked the presence of advanced professional degrees and the amount of work experience among the group of experts. In CLINT, the expert was a real estate lawyer with substantial work experience. In REVA, there were two experts: a theorist holding a doctorate and specializing in vibration theory and a plant engineer with more than thirty year experience. In LIFE UNDERWRITER, four senior underwriters, with more than 125 years of collective experience, and an M.D. comprised the expert group. In contrast, the experts for TELEX ROUTER were seasoned telegraphic clerks. These two factors of education and work experience were combined for measurement purposes as shown in Figure 1.

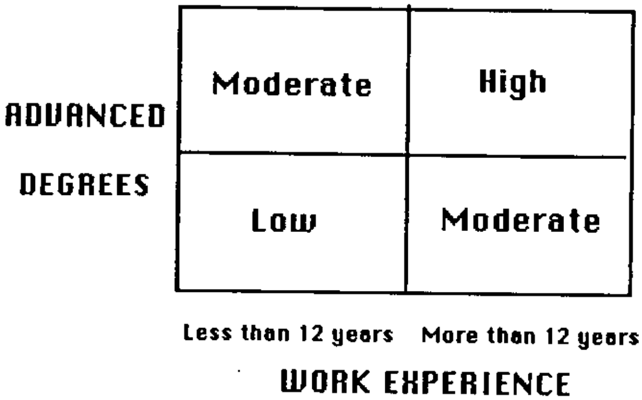

Figure 1. Depth of Domain

Rate of Change of Domain(s). This variable is an assessment of the degree to which the underlying disciplines or fields of expertise were changing through advancements in theory or application. Some domains are relatively fixed, others change only occasionally, and still other domains are in a continuous state of advancement. Interviews with the domain experts provided the measurement for this variable, where the degree of retraining required to remain proficient was the central point: Could an individual who was an expert in the domain five years ago and had added no new knowledge be proficient today?

4.2 Information Characteristics

It was deemed useful to distinguish between the characteristics of the underlying domain and those of the information inputs used by the system or experts in the decision process. In computerized decision-making, information is typically contained in database systems that are accessed by the expert system in the course of processing. As with domain complexity, we identified and measured factors contributing to information complexity.

Breadth/Scope of Information Inputs. Some expert systems may only require that the user answer a series of questions in order to gather the information needed for decision-making, while other systems require multiple basic information inputs at different stages of the processing and often these inputs are gathered from multiple sources. This difference is perhaps best illustrated by comparing the XCON system with the FX TRADER. The XCON system receives different types of information from the company's sales area (customer orders), its product engineers (component specifications), its manufacturing departments (cabling and other operational requirements), and lastly from its product/marketing managers. The information inputs are in a variety of different formats and are often entered at different time intervals. The sources of this information span six separate areas within the organization.

By comparison, the FX TRADER system requires one information input: the daily foreign exchange trades made at the bank. This information is entered through one source: a loaded tape of the days transactions.

To assess this concept of "breadth or scope" of information inputs, we counted the number of different information types employed and the diversity of sources from which the information was gathered. A measurement was then derived, illustrated in Figure 2.

TYPES	1 to 2	3 or more
3 +	Moderate	High
1 - 2	Low	Moderate
	SOURCES	

Figure 2. Breadth/Scope of Information Inputs

Ambiguity of Information. In the course of making a decision, an expert must at times interpret "raw" information in order to make informed judgments. At other times, the information inputs require no further interpretation. For example, in the XCON system, the information inputs are unambiguous; in the LIFE UNDERWRITER, the underwriter must frequently interpret information inputs, including medical examinations, financial statements, and family histories, in order to make an informed pricing decision. For the purposes of measurement, the authors defined three categories: no interpretation, some moderate level of interpretation, and high levels of interpretation.

Rate of Change of Information. Another factor is the degree to which the reference database(s), or categories of information inputs, change or are updated. Most expert systems are employed to solve a case or a problem, such as diagnosing a piece of equipment, underwriting an insurance application, or verifying a customer order in the examples above. These are "the transactions" of the system. To process these transactions, the expert system may have to access reference material or databases which describe or categorize the required information inputs.

A careful examination of an expert system will reveal that some systems employ reference type databases that are largely static while others employ highly dynamic databases. CLINT provides the user with a list of required documents for the completion of real estate loans in all 50 states. It uses a relatively static reference database, since legal codes and bank rules change infrequently. On the other hand, the XCON system operates within a highly dynamic information environment because the company is continually introducing new products and components, which create new categories of information inputs which must be added to the system before customer orders can be filled. LIFE UNDERWRITER represents a mix: some of the databases accessed (such as mortality tables) are fixed, while others change continuously (such as financial investigation files).

For the purpose of our framework, we distinguished between rates of change as never or rarely changing, sometimes changing, and frequently changing.

4.3 Decision Process Characteristics

The first two categories of variables examined the complexity of the knowledge "content" by focusing on both domain and information inputs. This third set of variables assesses the complexity of the problem solving "process" contained in a particular expert system, extending the thinking of Gory and Scott Morton (1971). We developed two measures in this area.

Breadth of the Decision Process. This variable seeks to capture the scope of the expert's decision process by tracking the number of functional or logical steps required to complete the process. A taxonomy of logical steps in problem solving was employed for this end and proved effective in our field studies for differentiating the more procedurally complex systems from those that were simpler. The taxonomy itself borrowed from the field of decision theory and has been applied to study noncomputerized areas of human reasoning (Shannon 1947; Newell and Simon 1972). Six possible generic activities that may be performed in the process of problem solving were postulated and then applied in the study of these expert systems to assess breadth.

1. The Definition Questions or Problems
2. The Development Specific Decision Criteria
3. The Development of Criteria Weightings
4. The Generation of Alternative Solutions
5. The Rating or Evaluation of Alternative Solutions
6. The Computation of an Optimal Solution

An expert system that encompasses any one or two of these logical steps might be considered "narrow" in the breadth of its decision-making. The TELEX ROUTER system, while handling thousands of messages per day, has a fairly simple underlying decision process that develops specific criteria for matching the right message with the receiver and taking action on that criteria. On the other hand, the LIFE UNDERWRITER encompasses all of these steps in the process of approving and pricing an insurance policy. We rated breadth in the following way: one to two, "narrow"; three to four, "moderate"; five or more, "high."

Newness of the Decision Process. All of the expert systems that we studied automate, to some extent, an existing process. Additionally, some proceed to create new processes that may greatly aid the organization. For measurement purposes, we differentiated between systems that strictly automated an existing process and those that also created new processes. For example, CLINT, the system that identified the required documents for a loan closing, created no new process for loan approval but greatly automated an existing process. XCON, however, has allowed the company to send components directly to the customer's location for installation and testing, rather than assemble and test the components first at one of the manufacturing plants and then repackage it for delivery. Organizational process improvements such as these can provide the biggest payoff in the implementation of a new technology.

5. DEFINING TECHNOLOGY COMPLEXITY

While there has been research conducted in the area of classifying problem-solving by various dimensions of complexity, very little research has been done for classifying the embodied technology of information systems according to complexity. Thus, research variables to assess technology complexity were created based on the authors' collective experience and through discussions with research participants. In designing these variables, no attempt was made to ascertain whether a company's choice of technology tools was optimal. Rather, the authors only wished to document and classify the technologies that had actually been used.

Diversity of Hardware Platforms. Expert systems may be built to operate on a wide range of hardware platforms, from mainframes to PCs. Creating an expert system for multiple platforms, or for a very special purpose computer, increases the difficulty of the development effort. Knowledge bases must be "ported" across environments, which often requires the recoding of rules or logic. Similarly, database queries must be made operational on the different platforms. The REVA development team has spent considerable energy porting the expert system across different platforms required by clients. Other systems in the pilot sample remain single platform systems, among them CLINT, FX TRADER, and TELEX ROUTER. LIFE UNDERWRITER and XCON run using several hardware platforms.

For the purposes of measurement, we differentiated between **development** and **delivery platforms** and gathered information only for the latter, i.e., the types of hardware on which the operational or production system was made to function for users. Additionally, we distinguished between the size of the computer (mainframe, minicomputer, microcomputer) and the chip architecture involved (a Motorola 68000 architecture versus a VAX chip set). The diversity of hardware platforms was derived using the matrix shown in Figure 3.

SIZE	ARCHITECTURE: 1	ARCHITECTURE: 2 or more
2 +	Moderate	High
1	Low	Moderate

Figure 3. Diversity of Hardware Platforms

The Scope of the Knowledge Base Programming Effort: The degree of difficulty in the encoding of the knowledge base acquired from experts is clearly a key factor in assessing the technical complexity of a project (Harmon, Maus and Morrissey 1988). Measuring that difficulty, however, proved challenging. One might consider measuring man-hours spent in development, but variations in programmer productivity make that measurement unreliable in comparing different systems. We decided to examine two factors: the number of "rules" (since most systems except for the simplest example-based systems employ some form of rule specification as a basic element of logic), and the total size of the "knowledge base," which, in more complex systems, will include "object" specifications as well as "rules."

Very effective expert systems may be created with fewer than a hundred "rules," as in the case of FX TRADER. On the other hand, systems can contain a very large number of rules. The LIFE UNDERWRITER contains approximately 1500 rules and XCON contains more than ten thousand. Then there are mid-sized systems, such as REVA, with several hundred logic rules.

The implications of the size of the knowledge base are reflected in the degree of difficulty associated with the initial system development and testing effort and equally, if not more importantly, with the difficulty of the knowledge maintenance task.

Looking only at the "rules" has obvious limitations. What one programmer might place into one "rule" another programmer might partition into a half dozen separate rules. Therefore, we also recorded the total size of the knowledge base in a given system. In doing this, we differentiated between the knowledge base itself and associated "databases" used by or within the expert system. The latter, i.e., the database portion of the system, is considered in another variable. Therefore, our method for deriving an assessment of the difficulty of the knowledge base programming effort involved counting the number of "rules" and the total "size of the knowledge base" as shown below.

	Personal	Small	Moderate	Large
Rules or	< 100	100-499	500-1499	> 1500
Size	< 100k	100-499k	500k-1.5Meg	> 1.5Meg

Using this measurement, both REVA and the FX TRADER are examples of "Small" systems with each system having about 100 rules and knowledge bases of less than half a megabyte. The LIFE UNDERWRITER was measured as "moderate," having approximately 1500 rules at the time of our study. "Large" is an understatement for XCON!

Diversity of Non-Inferencing Technologies. In a complete production expert system, it is often the case that the inferencing or reasoning portion is only one element of the overall system. We also sought to evaluate the diversity of other basic software technologies, the presence of which requires additional specialization in the programming team and is therefore important in understanding technological complexity. For example, two frequently encountered non-inferencing technologies in expert systems are database management systems (found in LIFE UNDERWRITER, TELEX ROUTER, and XCON) and graphics subsystems (found in REVA and FX TRADER). We factored out the presence of networking technology, which was set aside to be addressed separately. For measurement, we counted the number of other non-inferencing technologies embodied in the delivered systems and incorporated that number into the final measure of technological complexity.

Database Intensity. The distinction can be made between "knowledge" and "information" in the context of expert systems. In terms of evaluating technological complexity, the architecture of most complex expert systems also separates the knowledge component from the information components. Rules or other forms of logic encoding often request or read in information, typically stored within database management systems. To capture the addition to complexity that the database component of an expert system creates for the development team, both the cumulative size of the databases accessed by the expert system in the course of processing and the frequency of access to those databases were evaluated.

The dividing point of one megabyte of data for size seemed reasonable since beyond this point developers must begin to worry about optimizing access methods, transactions logging, access synchronization, and rigorous backup and recovery mechanisms. Measures of low, moderate, and high were derived using the scale shown in Figure 4.

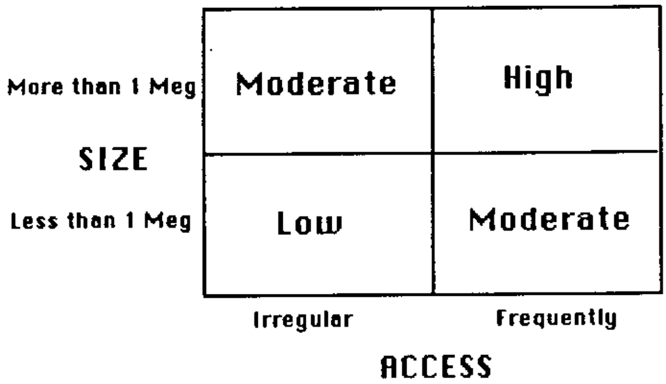

Figure 4. Database Intensity

As for the "access to data" variable, "irregular" was defined as loading in data primarily at the start of a user session or the absence of any database interaction within the expert system. For example, REVA accesses specific equipment component specification databases before an engineer proceeds with the question and answer consultation session to identify specific problems. The same is true with the FX TRADER, which reads in thousands of actual transactions before doing a batch statistical analysis of the data at the beginning of the user session. In contrast, the LIFE UNDERWRITER must access approximately a half dozen external databases in a typical user session.

Networking Intensity. This measure examines the use of computer networking for accessing other applications or databases by the expert system. It does not cover "networking" in the sense of making an expert system run on an MS-DOS network operating system such as Novell. This type of networking is simply a surrogate for a traditional time-shared operating system such as VMS or Unix.

One class of expert systems are those that are primarily "standalone" systems, operating on single computer and not employing any type of computer network either to receive data or send back results to another system. If external information is required in this type of system, it is loaded in from a tape or floppy, a technology that one might call "sneakerware." We labelled this level of networking intensity as "none."

An example of a "moderate" level of networking intensity is the LIFE UNDERWRITER. This system must access external databases over computer networks (to search for previously declined applicants or to perform financial audits) and must send its results, i.e., approved applications, up to the company's mainframe administrative systems for policy generation and billing. Its use of computer networks for the purposes of interacting with other databases or applications is organized into specific sessions.

The "high" category for networking intensity is clearly illustrated by TELEX ROUTER and XCON, both of which are networked with a number of separate internal and external systems in the normal course of processing.

6. APPLYING THE CLASSIFICATION FRAMEWORK

A structured research questionnaire was developed to gather data for each of the variables described above. In-depth discussions were conducted with the key people ("domain experts," "knowledge engineers" if any were employed on the project, and technical managers) involved in the six respective expert systems projects. The questionnaire data were then quantified, creating numerical values for each of the research variables. These values were summed for each system in each respective dimension of the framework. The next step was to plot the systems for each dimension on a grid (see Figures 5 and 6). The authors further refined the classification mapping, dividing the graph into quadrants by bisecting the "Knowledge" and "Technology" continuum at the midpoint scores for each dimension. This highlights four basic types of systems within the classification framework.

A first class of system, shown in Quadrant I, is one that is both restricted in its embodied knowledge and technologically simple. While none of the systems studied in the pilot sample were Quadrant I systems, many "personal" expert systems, developed with relatively limited expert system development shells for PCs, would fall in this quadrant. The common "benefit" of Quadrant 1 systems is to increase personal productivity. As a host of easy-to-use expert system development tools have emerged on the market, some of which require only that the user structure and enter a series of examples from which logic is derived, this type of expert system enters the realm of end-user computing.

The second type of system, fitting into Quadrant II, is one that is "knowledge intensive" yet uncomplex in its technology. Such systems incorporate highly skilled decision processes, typically running as standalone applications without extensive database access or networking. The target benefit of Quadrant II systems is often to enhance competitiveness by substantially improving decision-making in key business areas. CLINT is an example of such a system because it is domain-intensive but technologically simple. CLINT incorporates the knowledge of legal requirements and documents needed for real estate transactions across a variety of states. Its domain has a narrow focus but, at the same time, resolves often uncertain information through its knowledge base to achieve loan decisions. Technically, it is a standalone PC system with a small knowledge base and no database integration.

The FX TRADER also has a narrow focus, automating the foreign exchange auditing function of a large bank. Compared to CLINT, the information inputs for FX TRADER are certain. Actual foreign exchange transactions are filtered through the system for the identification of statistical outliers. These exceptions are then investigated by experienced auditors in another phase of the expert system that features a highly advanced graphics interface.

The third quadrant describes systems that computerize limited or narrow domains of simple or moderate sophistication but are none the less "technologically intensive." Such systems might have regular communications with larger administrative systems, accessing large databases, or might "ported" as part the development task to a number of different computer hardware environments. The target benefit of Quadrant III systems is organizational productivity and workflow improvement. Often, these benefits can help the organization enhance its competitiveness by improving customer service and organizational responsiveness.

REVA has a narrow focus: the stable field of vibration analysis as applied to a specific set of plant equipment. Its technological complexity has grown over the past year, however, as management has ported the system to different hardware platforms to meet client requirements. TELEX ROUTER is another example of a system that contains a relatively simple knowledge base that maps telex addresses to organizational locations but at the same time has high levels of networking and database integration. It is a production system that must work with international networks and adapt itself to constant reorganization inside the bank.

The fourth quadrant describes the most complex of systems, capturing highly specialized information and decision processes, with high integration and database requirements. The scope and cost of such development efforts warrant an ultimate benefit of substantially improved competitive position through a synthesis of improved decision-making and organizational productivity. LIFE UNDERWRITER, the most complex knowledge system, incorporates the "deep knowledge" contained in the medical, actuarial, and underwriting sciences involved in the underwriting process. The information gathered in the decision process is both broad (such as an individual's application, medical exams, and financial statements) and must be gathered from many different sources. Further, elements of this information are often uncertain, requiring that the expert and, by extension, the expert system interpret the raw data so that it may be meaningfully employed in underwriting. The decision process built into the computer system is also broad, spanning the gamut of defining investigative questions, developing decision criteria and weightings for these questions, and generating solutions, i.e., a risk rating for an applicant and premium pricing for a given type of insurance product.

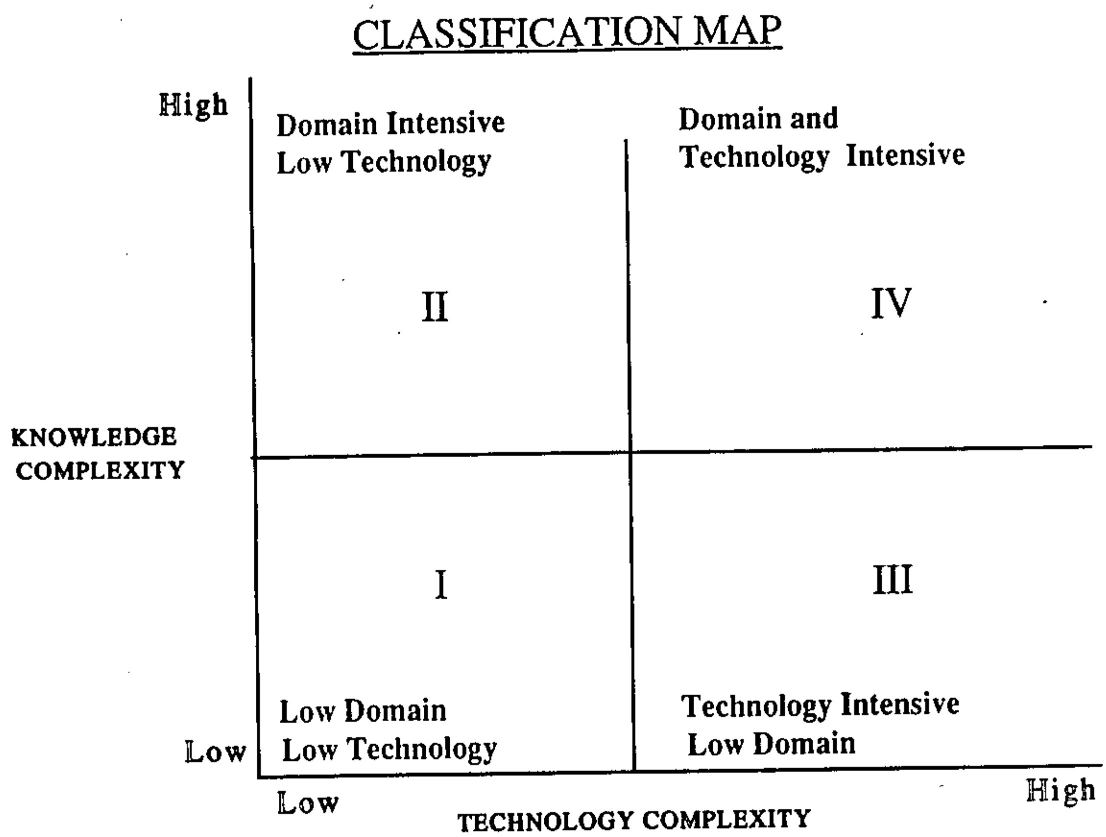

Figure 5. Classification Map

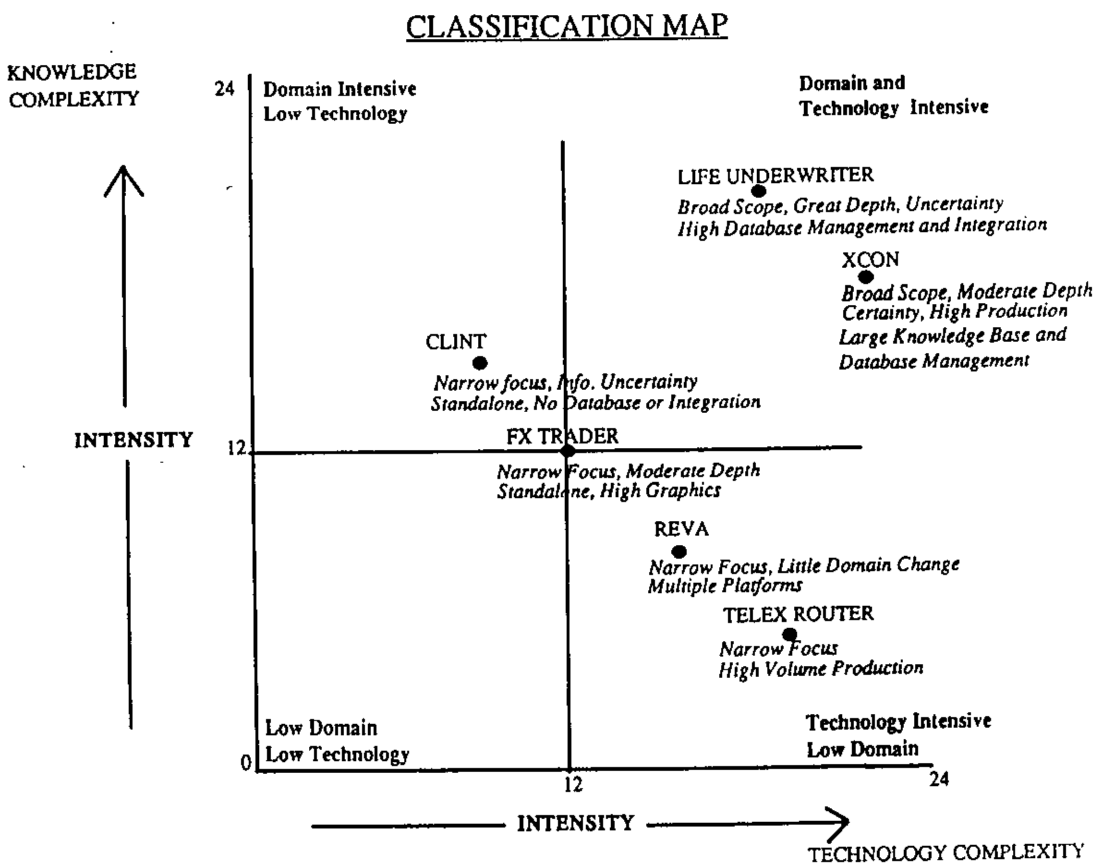

Figure 6. Classification Map with Expert Systems Plotted

Along the technological dimension, LIFE UNDERWRITER was also assessed as high due to the complexity of the database, knowledge base, and networking programming within the expert system.

XCON is impressive to any observer for its sheer size. All the products and components offered by the computer manufacturer are contained within the databases of this system. The logic of the system checks to see if components are compatible, if and how they can be installed in a given computer housing, and prepares installation instructions. Within our classification framework, XCON had high knowledge complexity primarily because of the breadth of the domains involved (manufacturing, product engineering, and product marketing) and the breadth of the information employed in the decision process gathered from many different areas in the company. However, unlike LIFE UNDERWRITER, XCON's information inputs, such as equipment specifications, have little uncertainty and require almost no additional interpretation. On other hand, the amount of these data, and the massive size of the "rule-base" that must be constantly updated for new product introductions, make XCON a most technologically complex system. The scope of the knowledge base, database, and networking programming efforts surpass any other system in our research consortium.

7. DISCUSSION OF FINDINGS

The classification framework provides a basis for managers to assess the complexity of a particular expert system along the two key dimensions of embodied knowledge and technology. This approach is consistent with previous management of technology frameworks (McKenney and McFarlan 1983). The benefits of this approach are threefold.

- Classifying expert systems in this way allows managers to assess the scope of the development effort and plan staffing and funding decisions accordingly. For example, the development effort for systems that are technologically complex and access other corporate databases are more likely to require the involvement of a professional programmer and some links with the corporate MIS group. The staffing required for this development effort is quite different than for a system such as CLINT, that, while sophisticated in a domain sense, operates in a stand alone environment and at least at this point requires no linkages with existing corporate databases.

- Using this classification approach allows managers to screen new development efforts and determine the "fit" between proposed projects and the company's existing initiatives in development. This enables managers to lay out a development strategy for expert systems that may include fostering projects with similar degrees of domain and technological complexity.

- The classification framework allows managers to fit an expert systems development strategy within an overall corporate strategy for systems development. If an organization, such as the company that developed LIFE UNDERWRITER, has an established in-house systems expertise, then undertaking a complex development effort such as that required for LIFE UNDERWRITER is both doable and in keeping with the firm's overall commitment to use information technology to achieve competitive advantage.

Managing complexity is always a key administrative task. Within the area of expert systems, defining the dimensions of that complexity is a first step toward establishing the critical management processes necessary to direct development efforts for competitive advantage. The framework we have presented provides that first step.

8. A FOUNDATION FOR FUTURE RESEARCH

We believe that there are many areas for which the classification framework described in this article can be employed as a foundation for further research and management thinking. We observed that the composition of development teams differed widely between systems in different quadrants of the model. Can staffing requirements be anticipated as a result of domain and technology complexity? Similarly, the organizational "home" or control point was different among the systems. For what type of system does a line or business unit control point make sense as opposed to a DP or corporate "skunk-works" cost center? Can a process for projecting the organizational productivity benefits of an expert system be created that factors in variations for different levels of domain and technology complexity? As expert systems technology has become more widely accessible to business, the challenge facing management is to effectively manage the development of these systems with strategies that are appropriate to specific systems. Frameworks such as that presented here contribute to the goal of making expert systems applications of the firm's competitive arsenal.

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