Expert Systems Usage: Task Change and Intrinsic Motivation[1]

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Abstract

What motivates use of an expert system? Recent studies have found that the anticipated performance benefits of using an expert system—such as increases in decision quality, consistency, and speed of decision making—can lead to increases in expected usage. But is motivation limited to performance benefits? Findings in job design theory suggest that other factors—such as increasing a user's sense of control over a task or making a task less routine—might also have an impact. If so, understanding these factors could be extremely valuable to managers seeking to build expert systems that will be readily accepted by users.

This paper synthesizes findings from expert systems, information systems, and job design research to model how the task change experienced by an expert systems user during adoption can affect that user's motivation to continue using the system. Using existing task constructs from the job design literature, a simplified version of the model is operationalized and tested on a data set of expert systems (all constructed in the early and mid-1980s) for which extensive quantitative and qualitative task-change data was available, as well as data on systems usage. The findings suggest significant relationships between the nature of the task changes associated with adoption and long-term usage of the systems, all consistent with the predictions of the job design literature. The study, therefore, concludes that a job design perspective of expert systems adoption can be a valuable tool in predicting user acceptance and, ultimately, systems usage.

Introduction

In recent years, the relationship between expert systems usage and user motivation has been considered in a number of empirical studies (e.g., Burton, et al., 1993; Byrd, 1992; Markus and Keil, 1994). The findings of these studies suggest that the usage of an expert system is likely to be motivated by the job performance benefits that a user expects to realize. But improved job performance may not be the only motivator. Some researchers propose that it may be beneficial to view expert systems adoption in the broader context of job redesign (e.g., Hauser and Hebert, 1992). Such redesign recognizes that while motivation can spring from achievement and the ability to recognize it (e.g., significance, identity), other intrinsic motivators also exist, such as the desire to retain or increase control over a job (e.g., autonomy) and the desire to maintain a certain level of cognitive stimulation from the job (e.g., variety, arousal).

This paper explores how the task changes experienced by a user impact that user's motivation to adopt an expert system. After reviewing relevant implementation and job design

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[1] Blake Ives was the accepting senior editor for this paper.

research, a two-stage model is proposed in which:

- The task changes that accompany the adoption of a system influence the user's motivation to use the system and

- The user's motivation, in turn, influences the likelihood of enduring adoption within the organization.

The model is operationalized using established constructs from the job design literature, particularly those developed for Hackman and Oldham's (1980) Job Diagnostic Survey (JDS) and Job Rating Form (JRF). An exploratory empirical test of the model is then described, using a data set of 66 expert systems for which detailed information on both the task changes accompanying adoption and levels of usage over time was available. The findings suggest that a broad range of intrinsic motivators—not just those relating to improved task performance—may influence long-term expert systems use.

Commercial Expert Systems Implementation Research

Since the mid-1980s, considerable research attention has been devoted to understanding the process of expert systems implementation in a commercial setting. Some earlier examples of expert systems implementation research involve the deployment of the XSEL system at Digital Equipment Corporation (Leonard-Barton, 1987) and the subsequent implementation process (Keil, 1991; Markus and Keil, 1994).[2] These later studies found that the system being examined had failed to achieve widespread usage despite strong performance, top management support, and recurring efforts to involve users in its design over an extended period of time (nearly 10

years). Moreover, these failures occurred in a company that had already developed one of the most successful expert systems of all time: the XCON system (Sviokla, 1986). Thus, the fate of XSEL graphically demonstrated an important fact about expert systems: the actual construction of an expert system—the focus of much early expert systems research (Gill, 1995)—can be far less daunting than the process of achieving acceptance for the completed system within the organization.

Many findings from information systems (IS) and decision support system (DSS) implementation research have also been applied to expert systems, such as:

- The benefits of user participation in expert systems design and implementation (Rees, 1993)

- The importance of top management support (Deschamps, 1992; Leonard-Barton, 1987)

- The potential impact of expert systems on job design (Hauser and Hebert, 1992)

- The need to match an expert system to the core competencies of the organization (Meyer and Curley, 1991)

- The importance of matching the expert systems interface to the user's cognitive skills (Lamberti and Wallace, 1990)

- The potential implications of the redistribution of power that could accompany expert systems adoption (Ryan, 1988)

Recent surveys also confirm the importance of the non-technical aspects of expert systems development. In a study of 45 expert systems applications (Tyran and George, 1993), managers reported the five most important factors for expert systems success to be:

1. Assessment of user needs
2. Commitment of human expert to the project

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2 System name is disguised in later articles.

3. Ease of expert systems use
4. Commitment of the user to the project
5. Top management support

Similarly, in a survey of artificial intelligence (AI) professionals, non-technical issues (e.g., oversell, lack of direction, business issues) were perceived to be far more serious road-blocks to AI success than technical problems (Coleman, 1993). Most recently, in a study of over 80 expert systems, neither technical success (i.e., the system performed the task adequately) nor economic success (i.e., use of the system saved money or generated revenue) were found to guarantee high levels of adoption or long-term use (Gill, 1995). In fact, for systems that fell into disuse, respondents were much more likely to cite problems of a non-technical, non-economic nature, as illustrated by Table 1.

Expert Systems Motivation and Usage

A particularly interesting stream of recent expert systems research has considered the impact of user motivation on usage. The research has emerged in two forms: a general form that views usage as a function of motivation without necessarily specifying the exact form of the relationship, e.g.,

$$Use = f(Motivation)$$

Table 1. Profile of Respondent Explanations for Systems Abandonment or Decline in Use (summarized from Gill, 1995)

Category	Explanation
Change in task	3 systems reported that a change in the nature of the task eliminated or reduced need for the system.
Costs of ongoing maintenance too expensive	4 systems reported that costs of ongoing maintenance was the major factor in the decline of use.
System became misaligned with the company computing environment	3 systems conflicted with the company's MIS environment.
Change in company focus or industry outlook	3 systems were impacted by changes in the company or industry-wide business situation.
Failure to recognize size of task domain	2 systems reported that the size of the task domain did not become apparent until initial development of the system was completed.
Solved a problem that wasn't perceived as critical by users	3 systems appeared to solve problems for which there was little user demand.
Subjected developer to potential liability	1 system was not used, in large part, because of potential liability concerns.
User resistance to externally developed systems (e.g., Not Invented Here syndrome)	6 systems reported that unwillingness of users to depend on systems developed elsewhere appeared to be the primary contributor to non-usage.
Unwillingness to take on development responsibilities	5 systems where no group within the organization could be found to take on development responsibilities.
Loss of key development personnel	8 systems reported that turnover among development personnel was the primary reason that systems use declined or ceased.

(DeSanctis, 1983) and a specific form, based upon expectancy theory (Vroom, 1964).

With respect to the general form of relationship between motivation and usage, a study of an order configuration system found that users failed to adopt an expert system for two reasons:

1. Sales reps were not motivated to do what the system enabled them to do.

2. Using the system made it harder to do what they were motivated to do (Markus and Keil, 1994. p. 13).

Thus, even though the system offered important benefits for the organization as a whole, the organization could not overcome the resistance of individual users who did not perceive those benefits as being particularly important to their individual jobs.

The motivation to adopt expert systems was also investigated for 74 knowledge engineers (Byrd, 1992). Improved productivity and elimination of routine tasks were found to be motivators for constructing expert systems, as well as benefits realized by users of those systems. The potential impact of expert-systems-induced task change on user motivation from a job redesign perspective has also been examined (Hauser and Hebert, 1992, p. 13), raising concerns that "reduced motivation and job satisfaction" may accompany expert systems adoption.

Expectancy theory has also been applied to assess user motivation to adopt expert systems (Burton, et al., 1993). Drawing upon previous IS research applying expectancy theory to decision support systems (DeSanctis, 1983), an experiment employing student subjects and a hypothetical system was used to assess how systems attributes impacted perceived motivation to adopt the system. The outcomes (valences) of better decision making, more frequent correct decision making, and better understanding of the job appeared to motivate perceived willingness to adopt.

Because the study of the relationship between motivation and expert systems adoption is relatively new, opportunities to extend the research in new directions abound. One such direction, as suggested by Hauser and Hebert (1992), is to draw upon the extensive literature that examines how task characteristics impact the nature of job performance (e.g., Aldag and Brief, 1979; Hackman and Oldham, 1980; Lawler, 1973; Thomas and Velthouse, 1990). A central theme of that literature is identifying factors impacting the worker's intrinsic motivation to perform a job. Such intrinsic motivation is viewed as being a function of the nature of the task being performed. As such, it can be distinguished from extrinsic motivation (e.g., motivation arising from the system of incentives presented to the task performer), which can often be manipulated without changing the task itself.

Although many specific characteristics that lead to intrinsic motivation have been identified in the management literature, most fall into one (or more) of three categories: control, arousal, and achievement.

Control

Sense of control over task activities, job, and organization are generally proposed to be motivating. Examples of proposed motivators include *autonomy* (Hackman and Oldham, 1980), *choice* (Thomas and Velthouse, 1990), *self-determination* of work pace, and *discretion* over work methods (Aldag and Brief, 1979). In practical terms, if using an expert systems increases the user's sense of control, a positive motivation to adopt would be anticipated. Conversely, if an expert systems increases the number of *prescribed activities* associated with a task, lack of motivation or active resistance to adoption could be anticipated.

Within the information systems literature, the importance of control has already been recognized, particularly during systems development (e.g., Barones and Louis, 1988). In addition, control has been specifically identified as a

factor motivating use of expert systems (Byrd, 1993; Hebert and Bradley, 1993).

Arousal

Arousal motivation stems from the individual's desire to achieve or maintain a particular mental state. Early motivation research, such as drive theory and reinforcement theory, viewed such motivation in terms of need satisfaction: the individual is driven to achieve a certain mental state until the need for that state is satisfied. In more recent research, however, it is recognized that the motivation to achieve a particular mental state is more complicated. For example, the partial achievement of a mental state may, in some cases, increase—rather than decrease—the individual's desire to achieve that state (Locke and Latham, 1994, p. 13). In addition, individuals often adapt to a particular mental state and may then lose the motivation to change it (Hackman and Oldham, 1980).

The most commonly described arousal motivator in task and job situations is the state of mental stimulation, also referred to as activation. Typical of arousal motivators, the stimulation-motivation relationship is generally presented as a U-shaped curve where the most motivating state appears to be in a band between too little stimulation—leading to boredom—and too much stimulation—leading to stress or even panic (Streufert and Streufert, 1978). Task and job characteristics that potentially change the level of stimulation associated with a task or job include *task complexity, goal difficulty* (Locke, et al., 1981), *variety* (Hackman and Oldham, 1980) and *increasing number of tasks* (Aldag and Brief, 1979). Since the acquisition of expertise will, over time, cause the amount of stimulation provided by a given task stimuli to decline (e.g., Hackman and Oldham, 1980, pp. 54-55; Norman, 1982, pp. 72-73) it is reasonable to expect that small upward changes in arousal brought about by expert systems use will tend to be motivating. Conversely, downward changes would tend to be demotivating.

Potential exceptions to the rule that increased arousal leads to increased motivation are easily visualized, however. For example, where the presystem task was already perceived to be excessively stressful, motivation to reduce, rather than increase, stimulation may exist. Similarly, large increases in stimulation may be resisted as a consequence of the U-shaped arousal-motivation relationship that is postulated.

In addition to its role as an independent source of motivation, arousal also plays an important role in moderating other sources of motivation. The individual's willingness to strive for high levels of other motivation sources, such as control or achievement, must ultimately be tempered by the increasing amount of mental effort required. For example, a manager's desire to control the specific acts of his or her subordinates is necessarily balanced by the cognitive demands that such control entails.

Achievement

The individual's own perception of performance (e.g. quality, competence, significance) is a commonly cited source of motivation. Such perception may be changed either through actual increases in performance, or through improving the performer's ability to identify his or her contribution to performance. Examples of task characteristics that fall under the achievement motivation heading include *task significance, task identity* (Hackman and Oldham, 1980), *impact, competence, meaningfulness* (Thomas and Velthouse, 1990) and *sense of responsibility* (Aldag and Brief, 1979). Most characteristics reflecting task performance (e.g., speed, consistency, quality) would also fall under the achievement heading. It therefore follows that where use of an expert systems increases the user's sense of achievement, motivation to adopt would be present. Conversely, where the expert systems reduces a user's sense of achievement—e.g., by reducing the user's sense of personal responsibility for work outcomes—resistance to adoption would be expected.

A Task-Change Model of Expert Systems Use

While the notion that the motivational character of an expert system will influence its use is straightforward enough, operationalizing the model presents some formidable obstacles. Chief among these is the problem of characterizing the task changes that occur when an expert system substitutes for (or augments) a human task performer.

A hypothetical case

When an expert system is adopted, many changes to the user's intrinsic motivation may occur simultaneously. To illustrate these changes, consider a hypothetical expert system in the task domain of medical diagnosis. Specifically, assume the system is provided by an HMO to a general practitioner to aid in initial diagnosis of patient conditions. Also suppose that its use is mandated by the organization. For a routine task case, such as diagnosing the flu, there would likely be little change in task complexity or sense of achievement resulting from system use—little of either was present in the presystem task. There would be some control impact, however, as the requirement to use the system would represent a loss of autonomy for the doctor. Further, if the doctor had to enter patient information into the system (and is not permitted to delegate that activity to a nurse), use of the system would increase the prescribed activities associated with the task case. In total, then, the motivational impact of using the system for routine cases would tend to be negative—although perhaps not unbearably so.

Non-routine cases present a very different situation. The task of medical diagnosis may be regarded as one whose primary focus is uncertainty reduction. There is, however, considerable discretion afforded to the physician regarding what questions to ask and tests to order. Using the hypothetical expert system, however, all such discretion would be removed, replaced with a prescribed activity

(i.e., entering symptoms and the results of tests performed at the behest of the system). The task complexity experienced by the doctor would also decline accordingly, as would the sense of responsibility for task outcomes (significance). Stated in motivational terms, then, large negative changes in both control and arousal would be experienced. Thus, unless the corresponding achievement benefits of using the system proved to be extraordinarily high (e.g., using it demonstrably saved lives and reduced malpractice insurance by $40,000 per year), such a system would be looked upon with extreme disfavor by its potential users—even granting that it did a good job in diagnosing. Parenthetically, precisely such a negative reaction to medical diagnostic systems has been commented upon in the expert systems literature (e.g., Carroll, 1987; Preece, 1990).

Task-level analysis

As the example illustrates, many motivation-related changes may accompany expert systems adoption. It is helpful to view the changes as occurring at two levels, a *task level* and a *job level.* Task-level analysis focuses on understanding the changes that occur to individual task cases as a consequence of expert systems usage. The concept of a case is the critical one here, as the motivation to use a system may differ widely between task cases. For example, while a doctor might view routine use of a system as a pest, the requirement to use the system in challenging cases might easily be construed as a threat to his or her integrity as a practitioner. For truly bizarre cases, on the other hand, the doctor—who would otherwise be at a loss on how to proceed—might welcome the system's advice. In other words, predicting the overall motivational impact of a system based on observing a single task case could easily lead to invalid conclusions.

Task-level analysis entails breaking the task into a set of characteristic cases, then analyzing each separately. The nature of the analysis to be performed involves understanding the

intrinsic motivation changes accompanying adoption, including:

* **Control:** At the task level, control can be operationalized in terms of *discretion* and *prescribed activities*. Task performers would be motivated to use expert systems increasing task discretion or reducing prescribed activities.

* **Arousal:** At the task level, the most important arousal motivator is the cognitive demands associated with the task case. The source of such cognitive demands is typically *task complexity* (Campbell, 1988). Since complexity is closely related to the knowledge required to perform a task (Wood, 1986), and that knowledge has been found to be an important source of intrinsic motivation (Campion and McClelland, 1993), it is reasonable to predict that moderate increases in task complexity brought about by adoption of an expert system will be motivating, while decreases will be demotivating. The exception could be situations where an expert system reduces the complexity of cases viewed by performers as overly stressful (i.e., where the motivation to reduce stimulation precedes adoption).

* **Achievement:** At the task level, achievement could be operationalized in terms of task performance measures, such as task performance *quality* and *speed*. Task performers would be motivated to use expert systems offering significant improvements in task performance.

Task-level analysis is most relevant to those task cases whose basic structure (e.g., inputs, outputs) is sufficiently unchanged by adoption to allow meaningful comparison of the before and after situations. The outcome of the analysis is a motivational assessment for each characteristic case considered. Such analysis is only a starting point, however. In order to ascertain the net motivational impact, the individual task-case impacts must be aggregated. In addition, motivation arising from other sources, such as changes in the mix of task

cases or changes in the scope of the task, must be accounted for. Such aggregation and consideration of additional motivational sources are performed in the course of job-level analysis.

Job-level analysis

The emphasis of job-level analysis is to assess the changes to an individual's job brought about by use of an expert system. Such changes would normally stem from two sources: (1) the impact of system use on the collection of tasks that are performed in the course of doing the job, and (2) the impact of use on a host of non-task-related factors, such as relationships with co-workers. While the latter changes may prove to be of critical importance, they tend to be very situation specific (and can change independently of the nature of the tasks being performed, much like extrinsic motivators). As a consequence, the present paper limits its attention to the analysis of first source: how expert systems adoption impacts the collection of tasks to be performed

To understand the changes that must be analyzed at the job level, it is helpful to group tasks into four general categories:

* **Target Tasks:** The tasks that are automated or supported by the expert systems application. It is the analysis of *individual cases* of changes to these tasks that is performed at the task level.

* **Upstream Tasks:** Tasks that directly or indirectly provide information (or other resources) to the target tasks.

* **Downstream Tasks:** Tasks that are directly or indirectly dependent upon information (or other resources) produced by the target tasks.

* **Collateral Tasks:** Tasks that are effectively unrelated to the target tasks.

The task collection components of a job are illustrated in Figure 1.

Analysis of change at the job level involves systematically considering the impact of the expert systems adoption for each of the categories of job-related task activities:

• **Target Task Changes:** While changes to individual task cases are considered at the task level, aggregation of task cases and accounting for changes in the type and mix of cases are performed at the job level. Thus, a system that screened out easy cases but passed the hard ones on to the expert could have a significant impact on the nature of the expert's job. For example, if the previously mentioned medical system was run by a nurse instead of a doctor and performed triage instead of full diagnosis, the attitude of the physician might well change dramatically. The system would no longer interfere with complex cases and might well save time on routine cases—all in all, a much more positive state of affairs. From a motivational standpoint, changes to task mix are likely to have a significant impact on *variety*. They could also impact *autonomy*. For example, the expert systems might serve to control the flow of tasks to the task performer, reducing the task performer's ability to schedule his or her own work.

• **Upstream and Downstream Task Changes:** The adoption of an expert system could significantly impact the starting point or ending point of a job. For example, a help desk system might make it possible for a customer representative to serve customer needs more fully, instead of being continually forced to route calls to technical support. Changes in upstream and downstream tasks can potentially impact such motivation-related characteristics as *task identity*, *variety*, *significance,* and *autonomy*.
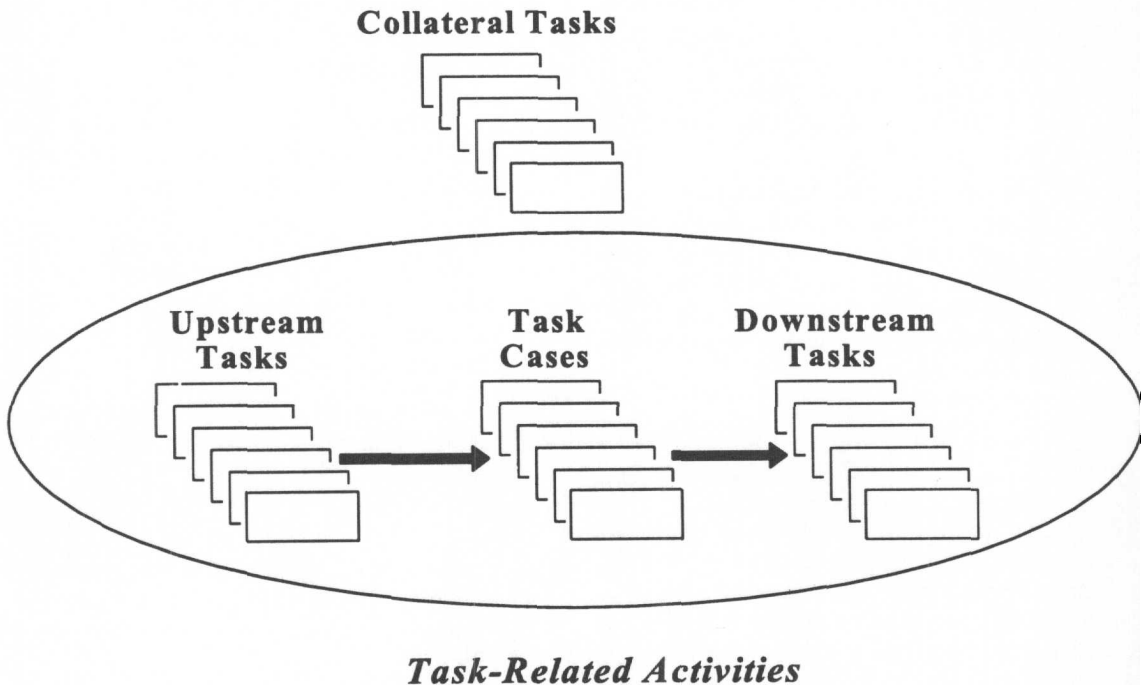

Figure 1. Components of the Job Level

• **Collateral Task Changes:** By altering the amount of time spent on task-related activities, a system may change the number and scope of collateral tasks associated with a job. The motivational character of these collateral duties, contrasted with the motivational character of the task being automated, would therefore be expected to influence the user's reaction to the expert system. Such changes, however, will tend to be situation specific, as collateral activities are, by definition, unrelated to the task being automated. Thus, two users might react very differently to a system that reduced target task performance time if one had enjoyable collateral duties to fill the free time created by the system, while the other had distasteful collateral duties.

Research questions

The task-change model of expert systems use can be summarized using two functional relationships:

1. Motivation to Adopt = f_1(Job-Level Changes, Task-Level Changes, Other Factors)

2. Usage = f_2(Motivation to Adopt, Other Factors)

The "other factors" in each expression is present to acknowledge that user motivation to adopt is unlikely to be the *only* factor determining systems usage. Similarly, job- and task-related changes are not the only factors influencing motivation. Extrinsic motivators, for example, are not incorporated within the model because they can vary independently of task. Such motivators, however, could clearly play a part in the overall motivation to adopt a system. For example, a user paid on a piecework basis might be more motivated to use a system that increased throughput than a user paid on an hourly basis.

The task-change model of usage asserts that a relationship between factors impacting intrinsic motivation and system usage should exist. In the context of this paper, it leads to two general research questions:

1. Is the overall motivation to adopt an expert system affected by the changes in intrinsic motivators accompanying adoption?

2. Does the overall motivation to adopt an expert system have an observable impact on the actual usage of that system?

As a practical matter—absent a specific theory for summing changes in individual motivators to determine an overall motivation—the questions are better broken down into a series of individual questions. For example:

1. Do increases in task discretion increase the likelihood of systems usage, while decreases in task discretion reduce that likelihood? (Control: Task Level)

2. Do moderate increases in task complexity increase the likelihood of systems usage, while drastic changes in task complexity, or complexity declines, reduce that likelihood? (Arousal: Task Level)

3. Do increases in task performance quality increase the likelihood of systems usage, while decreases in quality reduce that likelihood? (Achievement: Task Level)

4. Do increases in task performance speed increase the likelihood of systems usage, while decreases in speed reduce that likelihood? (Achievement: Task Level)

5. Do increases in autonomy increase the likelihood of systems usage, while decreases in autonomy reduce that likelihood? (Control: Job Level)

6. Do increases in variety increase the likelihood of systems usage, while decreases in variety reduce that likelihood? (Arousal: Job Level)

7. Do increases in significance increase the likelihood of systems usage, while decreases in significance reduce that likelihood? (Achievement: Job Level)

8. Do increases in identity increase the likelihood of systems usage, while decreases in identity reduce that likelihood? (Achievement: Job Level)

Naturally, these are only a subset of the questions that can be posed. Covering all three motivation categories for both job and task levels of analysis, however, they appear representative of the model in its entirety. As a result, these questions were specifically addressed in an exploratory investigation of the task-change model of expert systems use.

Exploratory Test: A Survey of Pre-1988 Expert Systems

A preliminary test of the task-change model of expert systems adoption was conducted using data from an exploratory study of the usage of early expert systems. The study investigated approximately 100 commercial expert systems drawn from a catalog that was included in Harmon, et al.'s (1988) *Expert Systems: Tools and Applications,* hereafter referred to as the "HMM sample." The research, which was conducted according to the procedure described in Appendix A, was based upon phone interviews that gathered a wide range of data relating to the performance, usage, and nature of each system.

Within the survey were questions specifically intended to gauge the types of task and job changes associated with each system's adoption. The questions were intended to provide rough estimates of how the adoption of each system affected:

- **Task Discretion:** As estimated by the degree to which the actions of the system were under the conscious control of the user.

- **Task Complexity:** As measured by the change in knowledge required to perform the task using the system, consistent with the component task complexity definition proposed by Wood (1986, p. 66).

- **Task Performance:** How use of the system impacted task performance on a variety of dimensions, including *quality of performance* and *speed of performance.*

- **Autonomy:** The degree to which decisions were under the control of the task performer, consistent with the definition of Hackman and Oldham (1980).

- **Variety:** The degree to which the task contained non-routine activities that varied from task to task, consistent with the definition of Hackman and Oldham (1980).

- **Significance:** The degree to which the task was perceived to affect the work of others, consistent with the definition of Hackman and Oldham (1980).

- **Identity:** The degree to which the work performed in the task constituted an identifiable whole, consistent with the definition of Hackman and Oldham (1980).

Although the survey was designed to utilize existing constructs, the nature of the study precluded taking full advantage of existing instruments, such as the JRF or JDS (Hackman and Oldham, 1980). Such instruments, although well established for measuring *task characteristics,* were not designed to measure *changes* in those characteristics. Further, practical constraints on the length of the survey instrument (which took an average of 45 minutes per system to administer over the phone) precluded incorporating repetitious questions in order to establish reliability. Therefore, accepting that the nature of the study was inherently exploratory, a modified set of task-change questions was devised (see Appendix B).

Results

Both quantitative and qualitative analysis of the data gathered for the survey of pre-1988 expert systems was performed. The quantitative component consisted of taking survey measures of task change and analyzing their relationship to measures of system adoption. The qualitative component consisted of identifying examples of expert systems where information from the respondent interviews—supplemented by information from available sources—supported or refuted the expected relationships. Results from both types of analysis are now presented.

Quantitative results

The task-change model of expert systems adoption predicts that a user's attitude toward a system will be influenced by the motivational character of the task change. That attitude, in turn, will influence usage. To test that model, the combined effect of the various task-change measures in the survey (independent variables) was analyzed with respect to two different measures of adoption (dependent variables):

1. **Maximum Usage:** Measured in terms of the maximum number of actual users compared with potential users over the life of the system. The choices consisted of:

   a. Unfinished prototype

   b. Completed prototype of application, never adopted within the organization

   c. Application completed and achieved only limited adoption by the organization or targeted customers

   d. Application completed and achieved moderate levels of adoption

   e. Application completed and achieved widespread or universal adoption among intended users

2. **Current Usage:** The degree to which the system was being used at the time of the survey. The current usage measure most closely reflected the *longevity* or *sustained use* of the system, as the survey was conducted at least five years after each system was developed. The choices consisted of:

   a. Never intended to be used

   b. Never been used

   c. Not presently in use

   d. In use by a number of users which has declined significantly from an earlier maximum level

   e. In use by a stable number of users at or near the maximum level

   f. In use by a number of users and use continues to grow

Two different sets of independent variables were selected for analysis. The first set used only the job-level constructs variety, identity, significance, and autonomy. Because these constructs have been used extensively in the literature (e.g., Hackman and Oldham, 1980), they represented the independent variables least subject to reliability and validity problems. A second, more comprehensive analysis used the job-level constructs augmented by task-level constructs that have not been validated. The variables for both analyses and their expected impact on adoption are presented in Table 2.

Table 2. Independent Variables and Their Expected Impact on Adoption

	Control	Arousal	Achievement
Task Level	Discretion (+)	Task Complexity (+)	Task Speed (+) Task Quality (+)
Job Level	Autonomy (+)	Task Variety (+)	Significance (+) Identity (+)

Consistent with the assumptions of the task-change model, only those systems where the task performer did not change after system adoption were initially included in the analysis (52 out of the 66 systems for which complete task-change information was collected). Also, because the dependent and independent variables were all discrete, probit analysis was used (Maddala, 1983). The results of the analysis are presented in Table 3 and Table 4.

Results of Analysis

The job-level analysis found both autonomy and identity to be significantly and positively

related to both measures of adoption. Variety was positively related to adoption in all analyses, however statistical significance was present only for the current use measure. No statistical significance could be attached to the job significance variable in any of the analyses. In part, that lack of significance was probably influenced by the relatively low variability in responses, with over 85 percent of respondents indicating that a decline in job significance accompanied expert systems adoption.

The combined analysis showed the same pattern of statistical significance for job level variables. In addition, it found discretion and complexity to be significant predictors of current usage, but not maximum usage. Speed and

Table 3. Probit Coefficients for Job-Change Variables (Independent Variables) and Measures of Adoption (Dependent Variables)

Variable	Expected Sign (Based on the Model)	Maximum Usage		Current Usage	
Autonomy	+	+0.723*	(t=2.02)	+1.259**	(t=3.53)
Variety	+	+0.149	(t=0.79)	+0.412*	(t=2.19)
Significance	+	+0.414	(t=0.96)	+0.253	(t=0.70)
Identity	+	+0.658*	(t=1.75)	+0.726*	(t=2.02)

Significances (using 1-tailed t test with 47 degrees of freedom): * 5% (t > 1.68); ** 1% (t > 2.41).

Table 4. Probit Coefficients for Both Job-Change and Task-Change Variables (Independent Variables) and Measures of Adoption (Dependent Variables)

Variable	Expected Sign (Based on the Model)	Maximum Usage		Current Usage	
Discretion	+	+0.151	(t=0.91)	+0.335*	(t=2.18)
Autonomy	+	+0.404#	(t=1.41)	+0.941**	(t=2.44)
Complexity	+	+0.144	(t=0.80)	+0.408*	(t=2.32)
Variety	+	+0.128	(t=0.66)	+0.412*	(t=2.14)
Speed	+	+0.108	(t=0.71)	+0.146	(t=0.96)
Quality	+	+0.262	(t=1.02)	+0.279	(t=1.10)
Significance	+	+0.377	(t=0.87)	+0.244	(t=0.66)
Identity	+	+0.723*	(t=1.85)	+0.951**	(t=2.69)

Significances (using 1-tailed t test with 43 degrees of freedom): # 10% (t > 1.30); * 5% (t > 1.68); ** 1% (t > 2.41).

quality were not significant predictors of either usage measure. As was the case for job significance, part of the lack of statistical significance may be attributed to the lack of variation in the speed and quality measures in the sample: only 13% of systems surveyed reported any declines in speed and there were no declines in quality reported.

Two findings of particular interest emerged from the analysis:

* **General agreement with the predictions of the task-change model:** For most of the variables (i.e., autonomy, variety, and identity for both models, discretion and complexity in the combined model), significance at the 5 percent level or greater was found with respect to the current usage dependent variable. The results for speed, quality, and task significance did not exhibit statistical significance, but were nonetheless positive (as predicted).

* **Differences between the two measures of adoption:** Although the general pattern of coefficients remained the same, there was, nonetheless a significant difference in the model's ability to predict maximum level of adoption contrasted with its ability to predict current use. That difference shows up in the significances of the coefficients for the task-change variables. It also showed up in the R-squared values when regression analysis, instead of the probit analysis, was performed. For example, in the combined model, the R-squared of the regression against the task and job characteristics in Table 4, was 0.184, which corrects to 0.032 when adjusted for degrees of freedom. For the current use dependent variable, on the other hand, the R-squared value was 0.425, which corrects to 0.318 when adjusted for degrees of freedom. Stated another way, the combined model appears to explain only about 3 percent of the variability of maximum usage for the systems in the sample, while it appears to explain about 32 percent of the variability in longevity of use. Thus, the findings suggest that *the motivational character of the task change associated with*

systems use may exert its greatest influence on long-term usage, rather than on initial adoption levels.

Further support that the above effects are somehow related to task change was found by manipulating the set of systems examined. As already mentioned, the set of systems analyzed was restricted to those where pre- and post-adoption task performers were the same (52 systems). There were, however, 14 additional observations for which complete data were available—those systems where a change in task performer accompanied adoption of the system (user-change systems). Because the nature of the task and job changes experienced by the latter set of users was not measured by the instrument, it was expected that job/task change data gathered for those systems would not be particularly relevant in predicting usage. As a test, the 14 user-change systems were added to the combined model regression. In the revised analysis, the significance of all coefficients but variety dropped below the 5 percent level (although maintaining the predicted sign). Further, the percent of variability explained (i.e., R-squared) for long-term usage dropped from 32 percent to 16 percent. Thus, the significance of the observed results appears to hold only for situations where an individual task performer experienced the task change associated with adoption.

Generalizability Issues

An important concern regarding the relevance of the results is the age of the systems surveyed. To what extent can findings relating to 10-year-old expert systems be expected to generalize to the expert systems applications of today? Today's expert systems—frequently embedded in larger applications and integrated with relational databases—often bear little resemblance to the early expert systems examined in the survey. The obvious danger, then, would be that certain types of job and task change could be correlated closely with specific expert systems technologies (e.g.,

systems built with the EMYCIN engine might always reduce discretion). Such a correlation could lead to task or job change acting as a proxy for the technology being employed. If so, the apparent effect of the job or task change could easily disappear in the event the technologies employed were changed.

In order to test the sensitivity of the model to the technologies employed, the analysis of the sample was performed again, controlling for a variety of technology-related factors. That analysis, described in detail in Appendix C, found that incorporating technology-related factors into the model had three pronounced effects:

1. It *strengthened* the significance of most of the task- and job-level variables.

2. Certain technology-related variables also showed significance. In particular, (a) expert systems embedded in other applications were more likely to be in use than standalone systems, and (b) systems constructed using PCs and, particularly, AI hardware were less likely to remain in use than systems constructed on minicomputers and mainframes.

3. The overall significance of the analysis was improved by incorporating the technological variables. For example, corrected R-squared of the combined job and task regression on the current usage variable rose from 32 percent to 54 percent.

These findings strongly suggest that the task- and job-level changes observed do have an impact independent of technology. They also suggest that the technology employed in building a system represents one of the "other factors" influencing usage proposed in the model.

Validity Issues

The apparent significance of the quantitative relationships observed must be tempered by obvious validity concerns. The primary depen-

dent variable, current usage, was largely factual in nature. As such, a high level of reliability can be expected (Kerlinger, 1986, p. 383). The same cannot be said about the independent variables, however. They measured a respondent's subjective assessments of changes that occurred many years before the interview. As such, their validity is in doubt.

One of the best ways to ensure the validity of survey responses is to use outside criteria to check the responses (Kerlinger, 1986). The gathering of available data prior to each interview and the discussions of systems that occurred during the course of each interview provided such criteria for assessing survey responses. Based upon these descriptions and discussions, the investigator was able to form a preliminary impression of how adoption of each system was likely to have changed the user's task. Where a reply to a survey question appeared to be inconsistent with that impression, the respondent was asked to explain the answer. In most cases, the respondent's explanation served to clarify the investigator's understanding of the system. In some cases, however, it was clear that the survey question had been misinterpreted by the respondent, at which point the question was explained and the respondent was given the opportunity to change the answer. While such checking does not constitute a guarantee of validity, it nonetheless served to reduce the likelihood of invalid responses resulting solely from survey questions being misunderstood.

Additional support for the validity of the results was provided through the case histories of specific systems where task-change-induced motivation appeared to impact systems usage. Identifying such examples was a key objective of the qualitative analysis of the survey data.

Qualitative results

Given the inherent limitations of any survey instrument in an exploratory research design, it is critical that any quantitative results be supported by qualitative observations. The analysis of descriptive materials and interview notes

yielded numerous examples of expert systems where the motivational character of the task and job change experienced appeared to contribute to system success. Some examples, grouped according to the motivation category they impacted, are now presented.

Control

According to the predictions of the task-change model of adoption, systems increasing their user's sense of control—either at the task level or job level—would be motivating and would therefore tend to be adopted by users. Systems reducing control, in contrast, would be demotivating and would therefore be subject to resistance from users.

Based upon survey responses, over 65 percent of the systems were accompanied by some loss of discretion, and approximately 80 percent were accompanied by some loss of autonomy. Such changes in control are predicted to be negatively motivating. There were, however, some interesting cases of systems successes where the user's sense of control was actually increased by adoption of the system, either through increasing discretion from other sources or through dramatically reducing prescribed activities associated with the task. For example:

- Coopers and Lybrand's *ExperTax* was constructed to guide field auditors in the collection of client data required for tax planning and accrual. Prior to adopting the system, these auditors had been directed in their task by tax experts located off-site, a process that often resulted in the auditors receiving incidental direction regarding *when* and *how* to gather specific data, in addition to *what* data needed to be gathered. After adoption, however, ExperTax provided the necessary direction regarding what information to gather. It was, however, designed to be extremely flexible regarding timing and methods employed. Thus, adoption of the system appeared to result in an actual increase in the job-level autonomy experienced by field auditors.

- Schlumberger's *Dipmeter Advisor* was an expert system designed to aid in the interpretation of the logs produced by lowering a dipmeter down an oil well shaft. Prior to adoption of the system, task performers had to manually draw complex tadpole charts, a process that could take days, before interpreting the logs. The system's built-in graphics took much of the drudgery out of the charting chore, which proved to be a major incentive for using the system. In fact, the system was eventually redesigned with its "expertise" at interpreting logs removed (largely at the request of users), leaving only its data processing and display features. Thus, the motivation to use the system appears to have derived from its ability to reduce prescribed activities associated with the task.

Arousal

The task-change model of adoption predicts that modest increases in arousal are likely to be motivating, while major changes in arousal—either increases or decreases—will be demotivating. These theoretical predictions are supported by empirical findings that suggest that moderate increases in task complexity, defined in terms of the amount of knowledge required to perform the task, and variety are sources of motivation (e.g., Campion and McClelland, 1993; Hackman and Oldham, 1980).

Within the sample as a whole, over 73 percent of the systems appeared to reduce the knowledge required to perform the task, which would tend to be demotivating. This finding is consistent with concerns that have been voiced with respect to the "deskilling" effects of some expert systems (Berry and Hart, 1990). There were, however, cases in which the arousal levels were too high prior to systems adoption, so the reduction in arousal was accepted—if not actually welcomed—by users. For example:

- Digital Equipment Corporation's *XCON* system was developed as a consequence of the

increasing difficulty associated with manual-
ly configuring VAX computers, brought
about by growing sales volumes, variety of
potential components, and complexity of
potential configurations. Prior to its adoption,
human configurers had been experiencing
increasingly high error rates (up to 70 per-
cent of the manual configurations had
errors) and had therefore been subject to
increasingly intense pressure to improve
performance. Use of the system dramatically
reduced these errors and speeded up
throughput (Sviokla, 1986).

Unlike task complexity, there was little evi-
dence of systematic reductions in variety from
systems use. Indeed, fewer than 10 percent of
the respondents reported decreases in variety.
Almost universally, the explanation given was
that systems took over most or all of the rou-
tine aspects of the jobs being performed,
allowing users to spend more time handling
the interesting parts of the job. For example:

• American Express' *Authorizer's Assistant*
  was used in the process of authorizing
  AMEX charges, providing users with a rec-
  ommendation based on data it gathered
  from various mainframe computers. Making
  the authorization decision prior to adopting
  the system involved manually accessing
  multiple databases, on several different
  computers—during which time the cardhold-
  er was usually waiting in some check out
  line. The result was an extraordinary sense
  of time pressure. The system greatly
  reduced the number of commands the
  authorizer had to type and, by automatically
  accessing the appropriate data and present-
  ing it on the screen, speeded up the entire
  process considerably. In addition, it also
  intercepted a significant percentage of calls
  and authorized them without human inter-
  vention.[3] Thus, the most routine task cases
  were eliminated from the task mix, making
  the mix of cases actually considered by the
  human authorizer more interesting.

  _____
  [3] AMEX specified that the actual percentage of automati-
  cally authorized cases should not be published.

Achievement

The task-change model of adoption predicts
that increases in achievement, either objective
or as perceived by users, will motivate adop-
tion. These would include both actual perfor-
mance improvements (e.g., speed, quality)
and improvements enhancing the performer's
ability to perceive and feel responsible for per-
formance (e.g., significance, identity). There
were many examples of systems that
appeared to enhance the sense of achieve-
ment experienced by users:

• A number of successful expert systems in
  the survey provided users with access to
  expertise beyond the levels ever possessed
  by a single individual. The *MACSYMA* sys-
  tem, for example, offered the user access to
  a broad range of tools and advice for per-
  forming symbolic integration. The range of
  expertise contained in the system was so
  great that it is doubtful *any* single expert
  could have acquired comparable skills in a
  lifetime.

• Increasing task identity, "the degree to which
  the task is done from beginning to end with
  a visible outcome" (Hackman and Oldham,
  1980), serves to make task achievement
  more tangible. Prior to the adoption of
  XCON (already discussed), for example,
  Digital had been forced to operate final
  assembly and test (FA&T) plants, in which
  VAX computers were assembled from man-
  ually produced configurations and errors
  corrected. The computers were then disas-
  sembled and shipped to customers. The use
  of *XCON* allowed for the elimination of FA&T
  procedures for most systems. Thus, it
  increased the identity of the configuration
  task by creating a direct link between config-
  uration and customer.

• In most of the examples cited, the task per-
  formers before and after systems adoption
  were the same. Thus, the relevant change
  was between pre- and post-system ver-
  sions of the same task. There were situa-
  tions, however, where adoption led to a
  change in task performer. In these cases,

the motivational character of the change experienced depended upon the previous job of the task performer. For example, Air Product's *Hazardous Chemical Advisor* was an expert system designed to determine proper packaging requirements for inter-state shipments of hazardous chemicals, based on a variety of regulations. Prior to its development, the task was routinely per-formed by experts in these regulations. After adoption, however, the task was per-formed by a former administrative assistant for whom use of the system represented a major increase in job significance.

Other Factors

The task-change model of adoption, as pre-sented earlier, presumed that other factors—outside of the task- and job-level motivators—would influence motivation and usage in some situations. The presence of these factors would be expected to lead to two types of examples:

1. Systems remaining in use despite appar-ently negative intrinsic motivation to adopt.

2. Systems abandoned despite apparently strong motivation to adopt.

Using survey responses, it was possible to identify examples of both types.

With respect to the first type of example—suc-cessful systems with negative motivation—there were no systems in the survey where all task- and job-change measures were negative. There were, however, three cases of systems that had not been abandoned where all four job-level variables considered appeared to be negative. The first case, Air Product's *Hazardous Chemical Advisor,* has already been discussed as an example where a change in systems performer accompanied adoption. A second system, AT&T's *Teresa,* performed background identification of faults in telephone trunk lines, displaying potential problems on a console and creating automat-

ed work orders for technicians. The task it per-formed was, essentially, a new task that could not have been previously performed by humans. The third system, Honeywell's *Mentor,* was a diagnostic system designed to help technicians maintain large centrifugal chiller air conditioning systems that Honeywell serviced on a contract basis. The system's demotivating job-level characteristics were, to a large extent, balanced by major task-level improvements in quality and performance time. In addition, the system greatly reduced the amount of log keeping required, particularly for routine task cases.

With respect to the second type of example—systems abandoned despite apparently posi-tive motivation to adopt—there were no cases that could be identified where all sources of motivation were positive. There were, howev-er, four cases of systems where net job level motivation appeared to be positive for identity and autonomy, yet the system had been aban-doned (or usage had declined significantly):

1. LISP-ITS, a tutorial system for the LISP programming language,

2. CBT Analyst, a program that aided users in choosing an appropriate computer-based training tool for a particular training situation,

3. TurboMac, a program that analyzed prob-lems in steam boilers, and

4. ONCOCIN, a program intended to direct doctors in chemotherapy treatments.

In all four cases, the clear consensus of respondents was that the cost of keeping the systems up to date, and not user resistance, precipitated the decision to discontinue the system. Because such costs of maintenance are not (typically) borne by actual systems users, they would not be expected to have a major impact on user motivation. As a result, they must be characterized as an "other factor" in predicting systems usage.

Another method used to identify other factors impacting use was to ask the opinions of the respondents themselves. Respondent comments suggested that there were a number of systems where task- and job-level change were not critical in determining usage. Examples include the following:

- GTE's *COMPASS* system was designed to diagnose problems in an electronic switch that was being discontinued, in order to avoid the need to continually train users in the maintenance of an obsolete technology. Similarly, NORCOMM's *MASK* system was designed to help the company's phone support personnel in answering questions from customers who encountered problems while using a new release of the company's screen I/O software. The need to diagnose such problems was eliminated by improvements made to the subsequent software release. In both cases, using the system provided users with a way of reducing the time required to learn tasks that were clearly going to become irrelevant to their organizations in the foreseeable future.

- Babcock and Wilcox's *Weld Scheduler* was developed to identify appropriate welding techniques to be used by field personnel in the installation and maintenance of fossil fuel boilers constructed by the company. An important reason cited for why the system was never deployed was that the group that chartered and participated in construction of the system was not the group that would have actually been required to use it. More generally, Gill (1995) reported six such systems where user resistance to systems developed by outsiders was cited by respondents as the most significant factor leading to system non-use.

- APEX's *PlanPower* expert systems was designed to create comprehensive financial plans for high net-worth individuals and was marketed to companies providing financial planning services. Early users of the system, while impressed with its capabilities, were unhappy with the way it disrupted information flows within the company (Sviokla,

1986). Ultimately, the combination of the organizational changes required of customers in order to use it effectively and the product's hefty price tag were major contributors to its demise.

These examples suggest that organizational issues, in general, are another critical "other factor" in determining usage, a finding consistent with nearly all IS implementation research.

Discussion

The exploratory analysis of survey data, both quantitative and qualitative, supports the position that the motivational character of the task change accompanying adoption of an expert systems significantly impacts use of the system—particularly over the long term. Such findings support speculation that "intrinsic rewards will have some impact on use" for information systems in general (Robey, 1979, p. 536). They also support the contention that user motivation accompanying expert systems adoption can be related to job design (Hauser and Hebert, 1992). These findings, however, come with issues of applicability and generalizability that need to be addressed. In addition, it is useful to consider some possible extensions to the model suggested by the systems surveyed.

Applicability

A number of applicability issues must be addressed regarding the findings from the survey of expert systems. First, the model proposed is a task-change model. As such, it is applicable only to predicting motivation of individuals who perform a given task before and after the expert system is put in place. If adoption of the system involves a change in performer, then the prediction of motivation becomes much more difficult, and the model cannot be blindly applied. The limitation of the model to same-performer cases may seem a serious shortcoming, especially as "textbook"

expert systems, such as described by Davis (1984), are proposed to be a way to replace scarce expertise. The survey itself, however, found that most systems (79 percent) fit the same-performer assumption. In addition, participants in the survey were nearly universal in their belief that the days of the standalone, do-it-all expert systems were numbered. Instead, they saw an increasing movement toward embedding expertise within conventional systems. For such systems, it is reasonable to expect that the percentage of same-performer situations will remain high.

Another important issue of applicability relates to the dependent variable considered in the study: expert systems use. Although use is certainly a prerequisite for the success of any information system, system success is often defined in more outcome-oriented terms, such as individual or organizational impact (DeLone and McClean, 1992). The survey made no attempt to measure these impact-related variables and therefore does not address these forms of success. Indeed, the findings of the survey raise an intriguing possibility: an expert system with sufficiently attractive control and arousal characteristics might be used even if task performance was not appreciably increased. Successful games, for example, are enjoyable precisely because such motivational factors are incorporated into their design (Hackman and Oldham, 1980).

Generalizability to other technologies

Although this paper has focused exclusively on expert systems, it is reasonable to ask whether the task-change model proposed might also be generalizable to other types of systems. There are two reasons for expecting that the model may also apply to other technologies:

1. The motivational model itself is not premised upon any technological assumptions. To the contrary, it is based upon findings that apply to job changes in general.

2. Within the realm of the expert systems surveyed, the results are quite robust for different technologies. Indeed, as discussed in Appendix C, incorporating technology into the model as an "other factor" actually strengthens the significance of the observed relationships. Such lack of dependence upon technology within the sample provides little basis for expecting such dependence will be present for technologies not included in the sample.

Thus, the possibility that the model might be broadly applicable to information systems should not be discounted. Further research would clearly be required before making such an assertion, however.

Extensions to the model

While the systems surveyed showed a statistically strong relationship between the task- and job-level variables and adoption, the qualitative analysis suggested that organizational factors played an important role, as well. Some of the findings also suggest that it might be possible to extend the proposed model of use to a third level: the organization level. Such an extension would have considerable justification in terms of organizational theory. Some examples are:

• **Control:** A number of proposed organizational motivators, including power (Lawrence and Lorsch, 1967) and avoiding dependency (Thompson, 1967) are readily characterized as control motivators. Within the sample of expert systems, Gill (1995) found six applications where failure to adopt appeared to stem from user unwillingness to become dependent on systems developed elsewhere (i.e., the "not invented here" syndrome).

• **Arousal:** Motivators such as seeking optimal organizational stress (March and Simon, 1958) and matching information processed to information processing capacity (Galbraith, 1973) have much in common with the arousal class. As noted in Table 1,

there were many systems where non-use appeared to arise from an organization-level desire to avoid taking on additional information processing responsibilities (e.g., the five systems where no organizational unit could be found to take on development responsibilities and the eight systems where loss of a developer precipitated systems abandonment). There were also three systems where declines in the industry appeared to reduce the need for the additional information processing capacity provided by the system.

• **Achievement:** Obvious achievement motivators—such as maximizing shareholder wealth (Weston and Brigham, 1978)—form the basis for much economic theory. Clearly, economic issues such as systems costs and financial benefits to the firm did play a part in determining usage (e.g., at least four systems were abandoned because ongoing maintenance was too expensive). Another important achievement motivator is congruence of activities with organizational goals (Thompson, 1967). As noted in Table 1, three systems were abandoned because users did not view the task they performed as particularly critical to the organization. In addition, the nine most successful systems in the sample—based on longevity, breadth of usage and amount of development effort invested—all fell into one of two categories:

1. Systems representing an important product of the organization using them (e.g., MACSYMA, Help, DASD Advisor), and

2. Systems contributing directly to the core activities of the business unit using them (e.g., Digital's XCON, American Express' Authorizer's Assistant, Coopers and Lybrand's ExperTax, Honeywell's Mentor, and AT&T's Teresa and ACE systems).

In all nine of these cases, the system's congruence with organizational goals is self-evident. Also supported is Meyer and Curley's (1991, p. 30) contention that "the most dynamic, suc-

cessful expert systems address some aspect of the 'core' of a company's competitiveness, rather than functions lying on the periphery."

The observed importance of organizational considerations in achieving systems adoption should not be interpreted as lessening the importance of task and job factors. Rather, it suggests that organizational motivation should be assessed in conjunction with motivation at the job and task levels. It may well prove that where the motivation to adopt an expert systems is strong on one level, weaker motivations on the other levels may suffice. Naturally, additional research into the interaction between motivation sources at different levels would be required before drawing such a conclusion.

Conclusions

Among the expert systems surveyed, a pattern of usage was repeatedly observed—a pattern closely resembling the one described by Markus and Keil (1994). An expert systems would be developed, favored with top management support, and, in most cases, demonstrated ability to improve the performance of its assigned task. The system would go on to achieve significant adoption within the organization, usually within a period of a year or two. Then, something strange would happen. Use of the system would decline—sometimes precipitously, sometimes gradually. Enthusiasm for continued development would wane. Usually, there would be a logical reason given for the decline in use, a reason often having little to do with the system itself. But, too often, the system would ultimately be abandoned.

About a quarter of the systems surveyed managed to avoid the pattern of decline, continuing to thrive for more than five years after they were built. One key reason, of course, was their superior task performance. No system in the survey failing to match presystem task performance made it past the prototype stage. But the same superior task performance was exhibited by the vast majority of abandoned systems as well. What made the surviving sys-

tems different was that, by design or by lucky accident, they did not focus merely on replicating or incrementally improving presystem task performance. Instead, they changed the task in ways that motivated use. They offered the user a greater sense of control. They increased variety or reduced routineness. They made it easier for the user to assess the impact of performing the task. They provided capabilities that made it possible for users to perform tasks at previously unheard of levels of proficiency. By enhancing these intrinsic motivators of control, arousal, and achievement, user commitment to these systems was assured. As a consequence, these systems were insulated against the various external factors that offered a convenient excuse for the abandonment of less motivating systems.

The implications of these findings should be clear to managers. The motivational effects of system-induced task change appear to be most pronounced with regard to long-term use. In other words, a manager will have fully invested in both constructing and deploying an expert system before the effects of lack of user motivation can be directly observed. By that time, it may be too late to fix the problem, as was the case for the system described by Markus and Keil (1994). Thus, as soon as the idea for an expert system has been conceived, it may be time to start assessing its potential impact on user motivation. Does it increase job scope or does it reduce it? How does it change the balance of routine and non-routine tasks for the typical user? Will using the system reduce prescribed activities associated with the task, or will it increase them? What other changes to the user's job will necessarily accompany adoption of the system, and how will they be perceived? Based on the answers to these questions, the manager can choose to proceed upon one of three paths:

• If adopting the system is expected to lead to increased motivation for the system's users, the development of the system can proceed rapidly. The results of the survey suggest such systems tend to have excellent levels of longevity and acceptance.

• If the motivation expected to accompany adoption is negative or mixed, it may be possible to redesign the application in a way that improves motivation. For example, a greater emphasis might be placed on automating task activities that are already mundane, as was done by the Dipmeter Advisor in the survey. Broader job responsibilities in other areas might be incorporated into user's jobs, as was done when many of XCON's user's became involved in system maintenance. In some cases, it might even make sense to change the intended users of the system from existing task performers to individuals who would view the opportunity to use the system as an increase in status.

• If the expected motivational impact of the system on its intended users remains negative, and redesign is not an option, the manager would do well to reconsider building the system. As clearly illustrated by the large long-term rate of abandonment for systems in the sample, systems where motivation is negative do not tend to last very long. Unless the benefits of such a system to the organization are extraordinarily high, it seems unlikely that management will be willing to commit itself to the tremendous level of oversight that will be required to keep the system operational in the face of long-term user resistance.

Naturally, in analyzing the motivational character of an application, a manager cannot ignore the system's potential economic benefits. The evidence of the survey, however, demonstrates that the motivational character of a system can be a critical determinant of long-term usage. A manager should therefore be skeptical of any rosy forecast of the benefits of an expert system that is demotivating to its users—unless, of course, that forecast includes the costs of a long, expensive, and, ultimately, fruitless implementation process.

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About the Author

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Appendix A

Expert Systems Survey Procedure

The survey of pre-1988 expert systems was conducted in order to gather data on expert systems at least five years after their initial development. Toward this end, a catalog of commercial systems— *Expert Systems: Tools and Applications* (Harmon, et al., 1988)—was chosen for detailed investigation. The protocol followed in conducting the survey is as follows:

- **System selection:** The entire HMM sample consisted of 115 systems. For practical reasons, only U.S. systems of an unclassified nature were investigated (97 systems).

- **Preinterview background research:** Prior to investigating each system, a systematic search of the expert systems literature was conducted to identify additional references to each system. The techniques employed included (1) searches of online databases, (2) consulting approximately 25 books on expert systems and five general MIS textbooks for references to each system, (3) examination of four additional catalogs of commercial systems prepared at about the same time period, and (4) acquiring materials prepared by vendors of the tools used to develop many of the systems. Typically, two-three additional references per system were identified in the background research process.

- **Respondent identification:** Once background research for a system was complete, the investigator attempted to identify an appropriate respondent to provide information on the current state of the system. The process for locating the most appropriate respondent for each system typically involved (1) contacting the company where the system was deployed, if known, (2) contacting authors of books or articles describing the system, if available, (3) contacting vendors of expert systems tools used to construct the system, and (4) contacting other respondents associated with systems in the same industry. The process of identifying a suitable respondent took an average of five hours per system. Of the 97 systems in the HMM sample, 16 could not be located, and 81 respondents were identified. These respondents came from a number of non-exclusive groups, including systems developers (50%), managers (66%), task experts (38%), systems users (17%), and systems support personnel (17%). Later analysis of results showed almost no relationship between respondent type and survey responses relating to system characteristics such as performance (Gill, 1995). Of the 81 respondents, there were five refusals to participate and one case where the respondent was both unable to determine if the system was still in use and unable to identify any person who could provide that information.

- **Interview:** Having identified the most appropriate respondent, a survey instrument was administered over the telephone to collect information that included written descriptions of each system, various success measurements (e.g., maximum degree of usage attained, status of usage at the time the survey was conducted, degree to which ongoing improvements and maintenance were in progress at the time of the survey), measures of system performance (e.g., speed, quality, consistency), characterizations of technologies employed, and a large number of responses relating to task changes accompanying systems adoption. Not all parts of the questionnaire could be administered to all respondents because, in some cases, systems in the catalog had not been completed or were not intended for use (10 systems). The amount of time taken to administer each survey ranged from 30 minutes to over two hours. During the process of conducting the interview, the system status and description were gathered first. In the subsequent sections, the investigator asked respondents to explain all answers that appeared inconsistent with the apparent nature of the system (as under-

stood by the investigator). They were then given the opportunity to change their responses in the event they perceived that they had misunderstood the question.

*   **Follow-up:** Upon completion of each interview, a system description was immediately prepared, and some investigator-coded questions were sent to the respondent for verification. Upon completion of the survey, a report summarizing the results and software for accessing systems descriptions and data were sent out to all participants.

The complete instrument and additional information on the research protocol can be found in Gill (1995).

Appendix B

Task- and Job-Change Questions

Scored on scale of: Strongly Disagree (1) to Strongly Agree (5)

1. Task Discretion:
While performing the task, the user must continually direct the system to perform whatever specific activities are desired

2. Task Complexity:
Use of the system significantly reduces the skills or knowledge required to successfully perform the task.

Scored on a scale of Much worse (1), Worse (2), Unchanged (3), Better (4), or Much better (5)

3. Task Performance
a. Average quality of task output or solution
b. Time or effort required to perform the task

Paired questions:
*   *First question determined pre-adoption level, scored Strongly Disagree (1) to Strongly Agree (5)*
*   *Second question determined change, scored Significantly Reduced (1) to Significantly Increased (5).*
*   *Actual change score used second score, adjusted for initial level*

4. Variety:
a. Prior to using the system: a substantial percentage of the task performer's time was spent on routine procedures which did not vary much from task to task.
b. After the system was adopted: how was the percentage of time spent on routine procedures affected?

5. Identity:

    a. Prior to using the system: the task was arranged such that a single task performer would not be involved in the task from beginning to end

    b. After the system was adopted: how was the ability of an individual to be involved in the task from beginning to end affected?

6. Significance:

    a. Prior to using the system: how well an individual performed the task had a significant impact upon the work of others or upon the quality of the product or service being delivered.

    b. After the system was adopted: how was impact of how well an individual performed affected?

7. Autonomy:

    a. Prior to using the system: the task performer often had to make important decisions regarding "what to do next" in the course of performing the task

    b. After the system was adopted: how was the number of important "what to do next" decisions to be made by the task performer affected?

Appendix C

Analysis of Sensitivity to Technology

In order to determine if the observed effects in the task-change model of expert systems usage were a result of task-change variables acting as proxies for technology-related factors, it was necessary to control for technology in the analysis. Fortunately, Harmon, et al. (1988) coded a number of technology-related variables. Specifically, they characterized each application according to:

a. **Application Size:** Coded as 1=Small, 2=Medium, 3=Large.

b. **Development Shell:** Three development shells—shell, language, hybrid environment—were coded as dummy variables.

c. **Representation:** Three representations—rules, induction and frames—were coded as dummy variables.

d. **Function:** Two interfaces—front end to existing application and enhanced conventional system (i.e., embedded)—were coded as dummy variables. The third, standalone, was omitted because of linear independence, and therefore constituted the base case.

e. **Input:** One input source—signal processing—was coded as a dummy variable. The second, dialog, was omitted because of linear independence and therefore constituted the base case.

f. **Delivery Hardware:** Three types of delivery hardware—minicomputer, AI workstation and main-frame—were coded as dummy variables. The fourth, PC, was omitted because of linear indepen-dence and therefore constituted the base case.

These variables, then, were used to control for technology in the analysis of task and job change. Conceptually, the results were expected to be consistent with one of the three following cases:

1. *If job and task changes were acting as proxies for technology in determining usage:* a substantial reduction in the significance of job- and task-change variables would be expected when technology-related variables were controlled for in the analysis. The overall significance of the analysis (e.g., r-squared) would increase moderately.

2. *If job and task change had an actual impact on usage, and technology had no impact:* the signifi-cance of job- and task-change variables should remain largely unchanged when technology-related variables were controlled for in the analysis. The overall significance of the analysis (e.g., r-squared) would remain the same or drop as degrees of freedom were lost.

3. *If job and task change had an actual impact on usage, and technology also had an impact:* the sig-nificance of job- and task-change variables would either remain the same or increase as apparent randomness in the dependent variable was reduced. In addition, technology-related coefficients would also show significance. The overall significance of the analysis (e.g., r-squared) would increase substantially.

The results of the analysis, summarized in Table C1 for the current use dependent variable, are clearly consistent with the third case. Specifically:

• Nearly all task- and job-change coefficients remained similar to their earlier values, and an increase in significance was experienced in most cases. Task quality also became significant. The only exception to the pattern was a decline in the significance of the variety coefficient for the extended (i.e., job and task level) model.

• Some technology-related significant relationships were observed. Among the most important of these:

    a. Induction-based systems were less likely to experience long-term usage than other types of systems. In part, such an effect is probably accounted for by the fact that early inductive expert systems tools, such as VP-Expert and 1st Class, were relatively unso-phisticated in their ability to induce rules from patterns in the data. As such, they tended to be favored by novice developers building small projects. As a result, there appears to be little reason to expect the finding to carry over to today's more advanced inductive tools, such as those employing case-based reasoning.

    b. Expert systems that enhanced conventional systems, rather than being deployed as standalone systems, appeared to experience higher levels of long-term usage. This effect may, in part, help explain the increasing popularity of embedded expert systems in today's commercial environment.

c. Minicomputer and mainframe-based systems experienced greater long-term usage than systems based upon PCs and, particularly, specialized AI workstations. This effect is consistent with the observed decline in the AI workstation market that occurred in the late 1980s. Similarly, PCs at the time of the survey tended to be relatively limited in terms of speed and addressable memory. The increase in the capabilities of PCs that has occurred since the time of the survey may render the effect less pronounced for today's systems.

• The overall significance of the analysis was substantially increased by including technology variables. For example, the corrected regression r-squared coefficient for the combined job and task model grew from 32% to 54% when the technology variables were added.

These findings lend credence to the view that the nature of task and job change accompanying adoption will impact expert systems usage and that the technologies employed in the system may also influence usage. In other words, the nature of the technology employed appears to constitute one of the "other factors" present in the model.

**Table C1. Probit Coefficients Relating Technology, Job-Change,
and Task-Change Variables to Current Usage**

Variable	Job-Change Model	Extended Model
Size (1=Small, 2=Medium, 3=Large)	-0.35	-0.23
Shell	+0.32	+0.35
Language	+0.12	+0.06
Environment	-0.28	-0.47
Rules	-0.52	-0.97
Induction	-1.95*	-1.73*
Frames	-0.83	-1.08
Front-end to existing system	+1.29	+0.39
Enhanced conventional system	+1.79*	+1.90***
Signal processing	-0.90	-1.00*
Minicomputer/workstation	+1.36*	+1.35**
AI Workstation	-0.09	-0.18
Mainframe	+1.72*	+1.18
Discretion	N/A	+0.40***
Autonomy	+1.64***	+0.73**
Complexity	N/A	+0.51***
Variety	+0.45*	+0.18
Speed	N/A	+0.13
Quality	N/A	+0.40*
Significance	+0.13	+0.26
Identity	+0.92*	+1.10***

Significances (using 1-tailed t test with 30 degrees of freedom):   * 5% (t > 1.69);   ** 1% (t > 2.46); *** 0.5% (t > 2.75).