INFORMATION FOR MONITORING:
A SIMPLE MODEL OF ITS VALUE AND
A NEW DETERMINATION TECHNIQUE

by

Michael Edmond Francis Treacy
B.A.Sc. University of Toronto
(1978)

Submitted to the Sloan School of Management
in Partial Fulfillment of the Requirements
of the Degree of

DOCTOR OF PHILOSOPHY

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

September 1983

Massachusetts Institute of Technology 1983

Signature of Author __________________________ Sloan School of Management
August 3, 1983

Certified by ________________________________ John F. Rockart
Chairman, Thesis Committee

Accepted by ________________________________ Richard L. Schmalensee
Chairman, Ph.D. Committee
ABSTRACT

INFORMATION FOR MONITORING:
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This work develops a model of the value of monitoring a situation, empirically tests the model, and illustrates its use in an information requirements technique for monitoring.

The model, based upon economic models of information value, indicates that the value of monitoring a situation is a product of three factors: situation criticality, the likelihood that the situation needs intervention, and the quality of available information.

This model was empirically tested using a cross sectional analysis of 304 monitored situations. Results indicate that a linear functional form is as powerful as the theoretically derived product form, that the three factors predict monitoring value very well and that situation criticality is the dominant factor in determining monitoring value.

These results lend strong theoretical and empirical support to Rockart's Critical Success Factors method for information requirements analysis.

Thesis Committee:  J.D.C. Little
                      S.E. Madnick
                      J.F. Rockart (Chairman)
I would like to sincerely thank the members of my thesis committee, John F. Rockart, John D.C. Little, and Stuart E. Madnick for their contributions to this research. Each has been an important source of ideas, encouragement, and friendship. In particular, Jack Rockart has helped to shape not just this work, but my entire view of the information systems field.

In addition to the committee members, Richard P. Bagozzi, Michael S. Scott Morton, and Peter G.W. Keen provided help along the way. This document might never have been signed, sealed, and delivered without the administrative support of Marion Walke. To each of them I offer my thanks.

Finally, I would like to especially thank my wife Evelyn. She fills my life with love and happiness and makes all the work and effort worthwhile.
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1 INFORMATION REQUIREMENTS ANALYSIS FOR MONITORING

1.1 Introduction

The analysis of information requirements is a classic MIS problem. It is a critical phase of the system life cycle, in which the most important element of the information system design is specified. More than three hundred articles have been published in this area. More than fifty techniques have been developed. As the field has broadened, the techniques for information requirements analysis have become more diverse.

The purpose of this present work is to develop a theoretically grounded technique for information requirements and to verify that technique with a strong empirical test. To accomplish this, we must narrow our focus upon a particular type of system or process for which information is required. A single information requirements analysis (IRA) technique cannot span the diversity of information systems in use today. By focusing upon information requirements for a particular process, specialized knowledge provided by research into that process can be applied to our work.

The process for which we shall choose to develop an IRA technique is managerial monitoring. It has been chosen for four reasons. First, monitoring is an important process, practiced widely by all levels of line management. [Sayles 1964; Mintzberg 1973] Second, there is specialized knowledge in this area. See, for example, Aguilar [1967]
and Pounds[1969]. Third, support systems can have a significant role in the support of monitoring activities. A recent study of executive level support systems [Rockart and Treacy 1980, 1981] found that systems at this level lent much of their support to the problem finding, monitoring process of management. Finally, monitoring is relatively easy to approach from the economic, mathematical modeling perspective that we wish to employ.

The leading technique for determining a manager's monitoring information needs is Rockart's Critical Success Factors Method.[Rockart, 1979] The method focuses attention upon the relatively few factors that are critical to the attainment of a managers' goals. These are the areas in which information is required. Successful application of the technique in dozens of field studies has provided informal verification of the technique. The technique appears to work, but the theoretical foundation for it is lacking. We do not know, for example, whether it is consistent with basic assumptions about managerial monitoring behavior.

This present work builds an information requirements analysis technique for managerial monitoring from the ground up. It uses the basic approach of Rockart's critical success factors method, which is to identify the factors or situations in which information should be provided to management for monitoring, but not the specific data that should be provided. The latter is almost always a matter of personal style, for which formal analysis techniques are of little use. To develop the new IRA technique, we begin with a set of definitions and assumptions that describe the monitoring process. Then, using the tools of information economics and mathematical modeling, two models of
the value of monitoring are reconstructed. One model assumes that the manager is a Bayesian information processor. The other is based upon a lens model of human information processing. The new IRA technique for monitoring is based upon the premise that if one can identify the situations that would be most valuable to monitor, then these are the ones for which information is required and to which managers should devote attention.

To test the validity of the monitoring value model, an instrument is developed to measure each of the important dependent and independent variables identified by the model. This instrument has general use beyond the current study. Here, it is used to collect data for a cross sectional analysis of the validity of the derived value of monitoring model. The results of the empirical work lend strong support for the value of monitoring model and for the new IRA technique for monitoring.

1.2 Objectives of the Thesis

This thesis provides four useful results for the field of MIS. It develops a simplified model of the value of monitoring, based upon earlier and more detailed models drawn from information economics. The simplifications increase the ease with which the model can be implemented and tested. The value model is in a form that can easily be extended through further study.

A second result that is obtained from this thesis is a new information requirements technique that is firmly footed in identifiable, testable assumptions. Although this new technique derives from completely different origins, surprisingly it provides
theoretical explanation and support for Rockart's critical success factors method.

The third result that obtains from this thesis is an instrument for measuring several characteristics of situations, information systems, and monitoring value. The instrument is reliable and valid. It is also generally useful beyond the current study, for it is measuring variables that have broad use beyond the study of information requirements.

Finally, the thesis provides an empirical investigation of the theoretically derived model of monitoring value. Sophisticated analytic techniques, such as linear structural equation modeling, are used to test the validity of the simplified model. The results of the study indicate strong support for the value of monitoring model and even stronger support for the validity of Rockart’s method.

1.3 Organization of the Thesis

This thesis is organized into six chapters. Chapter II provides a review of information requirements techniques. So many papers have been published in this area that a review of review papers is provided. Each of these has provided a categorization of IRA techniques and each of these categorizations is mapped into a new and simple framework. From this Rockart's critical success factors method is identified as the leading technique for IRA for monitoring. In the balance of the chapter this technique is reviewed in greater detail.

Chapter III sets the stage for the model development. It begins with a exploration of the relationships between monitoring,
information, and value. Then, a discussion of the strengths and weaknesses of the mathematical modeling approach is provided, both as a justification for its choice and so that potential problems inherent in the approach can be identified. Next, models of cost variance investigation are reviewed and discussed. Two of these models, one based on Bayesian information processing, the other on the lens model of information processing, provide useful models of monitoring. These are reconstructed on a common framework of definitions and assumptions.

Chapter IV analyzes the two models constructed in the previous chapter. From this analysis and empirical studies, a simpler model of monitoring value is developed. The model has three determinants of monitoring value: information quality, the probability that the situation needs managerial action, and situation criticality. This simpler model can be implemented as part of a new technique for determining information needs for monitoring. The chapter concludes with a description of this new technique.

Chapter V provides a set of empirical tests of the value of monitoring model. It begins with a description of the overall study and of the instrument used for measuring situation criticality, the probability of needing action, information quality, and monitoring value. Results confirm the reliability and validity of the instrument and three tests of the monitoring value model are performed. The first test examines the multiplicative form of the model and specifically tests whether a multiplicative form is more powerful than a simpler, linear form. The second test is of the power of the three independent variables to predict the value of monitoring a situation. The final test is of whether all three independent variables are necessary for
the model.

The thesis ends in Chapter VI with a discussions of the ramification of the findings and the opportunities for further research.
2 INDIVIDUAL INFORMATION REQUIREMENTS ANALYSIS FOR MONITORING

2.1 Introduction

Information is a fundamental ingredient of management. The creation, acquisition, communication, and consumption of information categorizes much of what managers do. [Mintzberg 1973] Without it, there can be no monitoring, no analysis, and no decision making. Indeed, without information there are no decisions to be made.

Yet, evidence indicates that many senior managers, although proficient at using information, have difficulties determining their information needs. As Ackoff has indicated, the problem is often not that a manager lacks relevant information, but that he suffers from an overabundance of irrelevant information that serves to obscure what is important. [Ackoff 1967] Davis reminds us of Herbert Simon's observations that humans are imperfect information processors, that their rationality is bounded, and that these human limitations constrain a manager's ability to determine his information needs. [Davis 1982] Perhaps senior managers have difficulties in determining their information requirements also because information is an abstract, global concept that is not easily aligned with concrete and particular management functions such as managing personnel, monitoring operations, and negotiating deals.

As might be expected, many techniques have been developed to aid managers in the determination of their information needs. These
generally fall under the rubric of information requirements analysis (IRA), a field that also includes information analysis for structured information systems design. In the next section, we shall review some of the IRA techniques that have been developed and provide a simple classification scheme with which to cluster them. Using Davis' model for the determination of an appropriate information requirements technique, we shall then proceed to isolate the class of techniques that is most suitable for our purpose: the determination of the information needed by senior managers to perform their monitoring functions.

2.2 An Overview of Information Requirements Analysis Techniques

We are concerned with techniques for the determination of monitoring information needs of managers. Not all IRA techniques apply only, or even primarily, to the determination of monitoring information needs. We shall include them in this review, though, so that our area of interest can be related to the broader field of information requirements analysis.

There are several detailed reviews of IRA techniques and each has produced a different typology. Because our concerns are narrowly focused upon monitoring, to the exclusion of other managerial activities that require information, an appropriate classification for our review is a composite of these typologies. In Table 2.1 we have listed the classifications of Bariff[1977], Munroe and Davis[1977],
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<td>report</td>
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<tr>
<td>decomposition</td>
<td></td>
<td></td>
<td>technique</td>
<td>deriving from existing info systems</td>
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<td></td>
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<td></td>
<td>key indicator</td>
<td>system</td>
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</tbody>
</table>

**DATA ANALYSIS**

- decision analysis
- decision tables
- activity analysis
- protocol analysis
- judgement models
- simulation

- decision analysis
- info flow analysis
- structured analysis
- syntactical analysis
- process analysis
- systems dynamics

- total study
- process

**ACTIVITY ANALYSIS**

- CSF analysis
- strategy set
- transformation
- critical factor
- analysis

**STRATEGY ANALYSIS**

- prototypes
- learning models
- discovery from an evolving system

**ADAPTIVE APPROACH**

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Figure 2.1

Information Requirements Analysis Techniques
Cooper and Swanson[1979], Rockart[1979] and Davis[1982]. The only other major review of IRA techniques, by Taggert and Tharp[1977], has not been included in Table 2.1, because the typology of techniques that was developed using cluster analysis is difficult to interpret. The IRA techniques in Table 2.1 have been grouped into four categories: data analysis, activity analysis, strategy analysis, and the adaptive approach. We shall consider each of these in turn. For examples of specific techniques, the reader is referred to these five reviews.

2.2.1 Data Analysis IRA techniques that fall into this category rely upon a manager's existing formal sources of information, such as files, reports, and memos, to identify the majority of information requirements. Unnecessary information contained in the sources is eliminated from the requirements list. Other types of information, identified by the manager as unsatisfied information needs, are added. Thus, the existing information supply serves as a base of requirements that is modified by marginal additions and deletions.

Chadler and Nador[1972] present a data analysis technique that they have used successfully to determine the information needed in a revised product information system for a manufacturing firm. Their approach was based upon surveys of a broad range of managers. From these surveys, information was gathered about existing documents that the managers create, use, or communicate to others. Information requirements were determined largely on the basis of these existing documents.

Rockart observed that one form of data analysis, the by-product technique, is the predominant method used to determine management
information needs. [Rockart 1979, p. 82] This technique is the basis for most formal management information reporting systems. Data generated as a by-product of transaction processing and operational systems is made available in reporting systems to management. Implicitly, management information needs are assumed to be some subset of internally available data.

The data analysis approach to information requirements identification has two major shortcomings. First there is little reason to believe that existing formal information sources satisfy the majority of a manager's monitoring information needs. For example, Mintzberg has observed, "the manager can expect little help in the performance of his monitor role from the traditional formal information systems." [Mintzberg 1973, p. 70] Thus, important information may be missed by data analysis because it was not among the information presently available. The second difficulty with data analysis techniques is that they do not adequately address the "overabundance of irrelevant information" problem raised by Ackoff. Data analysis techniques do not specify criteria for evaluating the importance of existing information, for classifying information as either 'necessary' or 'unnecessary'. They simply rely upon the unaided judgement of the manager. We seek a method that aids managers in that difficult judgement.

2.2.2 Activity Analysis The majority of IRA techniques are of this class. They attempt to analyze a manager's job as a series of activities and to identify specific steps required to complete each one. Most commonly, the series of activities is defined by different
types of decisions made by the manager. For every step in an activity, information requirements are gathered by analyzing the descriptive and normative information inputs needed for the execution of that step.

King and Cleland [1975] provide an example of this type of IRA analysis. Their technique, called the information analysis approach, is composed of several steps, beginning with the identification of the set of managers for whom the analysis is to be performed. These managers' jobs are decomposed into a set of decision areas which are each defined by a detailed set of decision steps. For each decision area, the decision steps and the managers' titles are used to form a table which summarizes the role of each manager in each decision step. Roles are categorized as one of initiation, execution, approval, consultation, supervision, or none. These same tables are used to build normative models of how the decisions should be made. Using the descriptive and normative models, a consensus is formed about changes in the decision processes. Once the consensus is formed, every decision step is decomposed to a level of detail that allows the identification of information requirements. Individual information requirements are then prescribed as the identified information for those decision steps that the consensual model indicates are relevant to the manager.

Most activity analysis techniques provide the methodology for structuring a manager's job as a series of activities. For lower level jobs, such as inventory controllers or payroll clerks, with clearly defined goals, responsibilities, and operating procedures, the methodologies provide useful results. However, for more unstructured jobs, as is typical of middle and senior management, the methodologies
often break down. Thus, activity analysis fails to equate very well with the needs of a manager trying to identify monitoring information needs. The huge number of potential situations for monitoring and the uncertainty as to how most of them relate to fuzzy managerial goals make monitoring activities unamenable to formal, top-down analysis. We seek a method that aids a manager in providing partial structure to the analysis of his or her monitoring activities, without insensitivity to the fundamentally fuzzy nature of those activities.

2.2.3 Strategy Analysis IRA techniques that are of this class do not rely upon existing information sources, nor do they require managers to structure their jobs into sets of activities. These techniques focus upon the strategies that the manager is using to achieve his goals and define information requirements as the information necessary to manage those strategies. It is implicitly assumed that strategy management includes all the most important functions that managers perform and that these functions determine the relevant information needs.

The Critical Success Factor technique is the leading strategy analysis technique. It was developed by Rockart[1979] in response to the need for an IRA technique that was appropriate for middle and upper level managers, dissatisfied with the usefulness of their formal information sources in their poorly structured roles. The technique does not rely upon existing information sources, nor does it require managers to structure their jobs into sets of activities. Instead, a manager records personal goals and objectives, as best he can, and identifies "the areas in which good performance is necessary to ensure attainment of those goals."[Rockart 1979, p. 85] Those areas are the
underlying critical success factors. Goals and CSF's are reconsidered in an iterative manner until the manager is satisfied with the results. Information requirements are then defined as the information necessary to be able to monitor and manage the identified critical success factors.

The CSF technique provides only enough structure to the IRA process so that only someone intimately knowledgable of the manager's goals, role, and situation can apply it. Thus, it demands that the manager, for whom the information requirements are being analyzed, be the central active participant. The CSF technique minimizes the rigidity with which a manager's role is analyzed. Therefore, it has been applied most successfully with middle and senior managers whose jobs are somewhat unstructured. For lower level personnel, with rigid, structured roles in the organization, the technique is clumsy to apply.

The quality of results that obtain from the CSF technique are crucially dependent upon the quality of the analysis performed by the central participant, the manager. An attempt is made to control for this potential problem by requiring that a trained CSF analyst aid the manager in working through his critical success factors and subsequent information needs.

2.2.4 Adaptive Approach The adaptive approach to information requirements analysis emphasizes the process of improving information, rather than any particular analytical technique. A prototype information system is built and initial use by the manager induces learning which results in new or clarified information needs. Marginal changes in the information source are made to satisfy these needs and
use by the manager continues to produce new unmet needs. An adaptable information system and close attention to these new requirements allow a rapid evolution of both a manager's perceived information requirements and the system to satisfy those needs.

The adaptive approach is not in direct conflict with any of the previous IRA techniques. Instead, it provides a complementary perspective that recognizes that one pass of any of these techniques provides only a partial analysis of information requirements.

Many specific IRA techniques, such as CSF analysis, embrace an adaptive approach by recognizing the need for iterative analysis. Specific techniques play an important role in adaptive IRA approaches, both in establishing the initial prototype and in aiding managerial understanding and learning. The adaptive approach should be embraced without denigrating the importance of specific information requirements analysis techniques.

2.3 IRA Techniques and Monitoring Information Needs

The four groups of information requirements analysis techniques differ in focus, emphasis, and applicability to our particular area of interest: monitoring information needs for senior managers. Data analysis techniques are well suited for the analysis of information needs for stable, well structured, and simple situations (see Table 2.2). For example, an inventory manager in charge of a mature, well defined business function, will find the majority of his information needs in existing available information. Most of his needs derive from the information needed for the structured activities that
comprise his role and in a mature, structured role this information is already available. In other types of roles, data analysis techniques present difficulties. If the role of a manager is unstable, if his tasks are uncertain, then existing information will reflect past information needs, not present or future ones. If the role is not well structured, then available information is not easily associated with tasks and it is exceedingly difficult to decide, using data analysis techniques, which information, of all that is available, is necessary.

Even if a role is stable and well structured, it may be sufficiently complex that the identification of necessary information using data analysis techniques is difficult. In this case, activity analysis is more appropriate, since a comprehensive, top-down information analysis strategy handles complexity well. Activity analysis is usually a long undertaking since it requires comprehensive consideration of the activities that comprise a role. These techniques are not easily applied in an iterative, adaptive approach. Thus, valid information requirements from an activity analysis depend upon a stable set of activities. As well, the techniques apply only when there is a high degree of structure in the manager's role, since unstructured activities are not amenable to comprehensive analysis.

Monitoring activities of senior managers are not very structured. [Aguilar 1967, Anthony 1965] There is no textbook description of how a manager should monitor his functions. The monitoring activities of senior managers are also quite changeable. [Aguilar 1967] What is important to monitor in one week may be unimportant in the next. Mintzberg observed that in each working day the manager encounters a great variety of fragmentary
activities. [Mintzberg 1973, p. 31] Thus, data and activity analysis techniques, which yield valid results only for well structured, stable roles, are not appropriate for the determination of the information needs for senior managers in their monitoring activities.

Davis [1982] presents a qualitative model for the selection of an appropriate IRA technique which suggests the same conclusion. The model is based upon his classification of IRA techniques, as shown in Table 2.1. Stated simply, it implies that the more uncertain the requirements process, the further down his list of IRA techniques one should choose. Overall requirements process uncertainty is obtained from summing the uncertainty associated with the existence and stability of a set of requirements, the ability of the users to specify requirements, and the ability of analysts to elicit and evaluate requirements. The assessment of senior managers' monitoring information needs presents difficulties in all three areas. Thus, overall requirements process uncertainty would place us well down Davis' list of IRA techniques, precluding the use of data analysis or activity analysis techniques.

This leaves few IRA techniques from which to choose. As has been discussed, the adaptive approaches, such as prototyping and discovery from an evolving system, describe an approach to the process of information needs analysis rather than a specific analytic technique. Given the instability of requirements, an appropriate technique should probably be adaptive, but what technique that should be is yet unresolved.

The critical success factor (CSF) technique is the leading technique between activity analysis and adaptive approaches. It was
developed specifically for the problem at hand, the determination of monitoring information needs for senior managers, because existing techniques offered such poor solutions. Keys to the success of this technique have been the minimal structure that it imposes upon the analysis of a manager's role and the orientation toward strategic issues. The CSF technique was developed from wisdom and experience, yet it has not undergone rigorous analysis. In the next section, we highlight some possible reasons why we might wish to do so.

<table>
<thead>
<tr>
<th>Characteristics of Roles Most Suited To Each Group Of IRA Techniques</th>
<th>STABILITY</th>
<th>STRUCTURE</th>
<th>COMPLEXITY</th>
</tr>
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<tbody>
<tr>
<td>Data Analysis</td>
<td>high</td>
<td>high</td>
<td>low</td>
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<tr>
<td>Activity Analysis</td>
<td>high</td>
<td>high</td>
<td>high</td>
</tr>
<tr>
<td>Strategy Analysis</td>
<td>medium</td>
<td>low</td>
<td>medium</td>
</tr>
<tr>
<td>Adaptive Approach</td>
<td>low</td>
<td>low</td>
<td>medium</td>
</tr>
</tbody>
</table>

2.4 Assessment of the CSF Technique

The critical success factor technique was first introduced to the management literature in 1961 by D. Ronald Daniel. He wrote, "a company's information system must be discriminating and selective. It should focus on 'success factors'. In most industries there are
usually three to six factors that determine success; these key jobs must be done exceedingly well for a company to be successful." [Daniel 1961, p. 116] Daniel's idea reflects a much earlier thought of the Italian economist Vilfredo Pareto. Pareto wrote, "In any human endeavor with multiple variables, often three or four can make the difference between success and failure."

Rockart picked up Daniel's idea of success factors and expanded it. He identified five major sources of critical success factors, industry structure, competitive position, environmental factors, individuals' views of their roles, and temporal factors, and provided a clear definition of CSFs and their link to information needs.

"Critical success factors thus are, for any business the limited number of areas in which the results, if they are satisfactory, will ensure successful competitive performance for the organization... As a result, the critical success factors are areas that should receive constant and careful attention from management. The current status of performance in each area should be continually measured and that information should be made available." [Rockart 1979, p. 85]

The CSF technique has grown enormously in popularity and use since Rockart's article. At present, more than a dozen consulting firms use the critical success factors technique to analyze clients' information needs. The list of companies includes Arthur Anderson, Arthur Young, Booz Allen, Index Systems, and Price Waterhouse. Both IBM and Honeywell, major computer vendors, have included the CSF technique in recent revisions of their information systems planning methodology.

The CSF technique has been adapted for many uses in several different types of management analyses. Munroe and Wheeler [1980] have
discussed the use of critical success factors analysis in strategic planning.

The technique is adaptable to several analyses because it is based upon concepts that are not specific to information requirements analysis. Critical success factors are not equivalent to information needs. They are situations that should interest managers. It follows that senior managers should monitor these situations, using several specific types of information that may be determined by personal style and preference. But it follows just as clearly that critical success factors should be considered when planning and that they can be important dimensions for management control. Thus, CSF analysis results not in a list of specific pieces of information necessary for senior management monitoring, but in a list of situations that should be of interest to senior managers. The specific measures that managers would monitor are usually determined by personal style and preference.

That one should monitor those situations critical to successful performance seems almost tautological. Yet the consistent application of this rule for information requirements analysis results in several apparent paradoxes that indicate that the rule may be incomplete. Consider, for example, a situation described as 'the quality of the executive group.' This situation is critical to successful competitive performance in most organizations. Without high caliber executives, a firm may be outmaneuvered by its competitors and fall into economic decline. But, one would rarely find 'the quality of the executive group' among a CEO's critical success factors, an apparent violation of the CSF rule. Why isn't it on most CEOs' lists? Not through oversight, surely, but rather because the quality of the executive
group is such a stable situation that it rarely creates problems. Thus, not only must a situation be fairly critical to performance for it to be worth monitoring, but it also appears that its condition must be somewhat volatile, so that there is some potential need for attention to this important situation. Stable situations do not offer that potential.

On some CEOs' CSF lists, 'the quality of the executive group' might appear as a temporal factor, one that is on the list because of the specific circumstances of the firm. What might those circumstances be? The crash of the executive jet results in the death of four key executives. A group of executives leaves to join a competing firm. The newly arrived CEO finds that the executive group is old and stodgy and doesn't match his aggressive style. In each of these cases, the situation is no more critical to successful performance than before a problem occurred; quality executives are always critical to success. What has changed is the likelihood that the CEO has a problem. The situation, we shall say, has become more volatile.

Consider another example. Let's assume that a CEO has two situations equally volatile and equally critical to success: 'management of working capital' and 'competitors product developments'. The first situation is characteristically easy to monitor because good data about that situation, good measures in the CSF lexicon, are readily provided by the accounting system. The second situation is inherently difficult to monitor because good data are not readily available. Intelligence may be gathered on competitive developments and educated forecasts may be made, but the obtained information will never be of a quality equal to that available for the management of
Given these facts, should the CEO be equally concerned about monitoring these two situations? To help decide this, let's make the difference more extreme. Assume that it is impossible to obtain any information on the second situation. What use is there then for the CEO to attempt to monitor that situation? None. Therefore, the value that one obtains from monitoring a situation appears to depend not only upon the criticality and volatility of the situation, but also upon the quality of information that is obtainable about the situation. If the information is of lower quality, then the inherent value of monitoring is lower, for value derives from the information used for monitoring.

If information of equal quality could be provided for every situation, then it would not arise as an issue in CSF analysis. This provision appears to be an implicit assumption of the technique. We have shown by example, though, that attainable information quality varies from situation to situation. Some are just inherently difficult to measure. For others, information is readily available in abundance and in detail.

These apparent inconsistencies in results obtained from CSF analysis strongly suggest that the technique may be based upon an incomplete rule, that there are characteristics of situations, dimensions other than criticality, that are important determinants of which situations should be monitored. In particular, we have identified situation volatility and information quality as two characteristics of situations that impact their importance for monitoring. Our evidence is purely anecdotal. There may be other characteristics that are important. These two may be incorrect.
Further theoretical and empirical inquiry is necessary before a clearer picture can be formed.

2.5 Conclusions

Critical success factors analysis is the leading IRA technique for determining managers' monitoring information needs. Because of the unstable and unstructured nature of those needs, CSF analysis has proven itself superior to the multitude of other data analysis and activity analysis techniques. These other techniques tend to overstructure the analysis process. A unique strength of the CSF technique is its ability to provide a minimal and flexible structure, yet to gain very powerful insights into the information needs of managers.

Yet, the CSF technique is not without its imperfections. The fundamental rule of this technique is that one should monitor those situations most critical to successful performance, but the consistent application of this rule sometimes leads to paradoxical results. One explanation for these results is that the rule is incomplete, that there are important characteristics of situations, other than criticality, that are not being taken into consideration. Two potentially important characteristics that have been identified are situation volatility and information quality.

Another difficulty with the CSF technique is that it lacks a theoretical basis. The technique was initially developed and has been enhanced through wisdom and experience. It enjoys widespread, successful application, yet the lack of theoretical underpinnings
results in three limitations. The first is that the technique is exceedingly difficult to examine and to validate. Assumptions are not obvious. The fundamental rule is not derived, but simply stated. The completeness of the rule can only be tested in the most informal and incomplete fashion.

A second limitation that derives from the lack of theoretical foundation, is the technique’s disconnectedness from existing bodies of management theory. How does critical success factor analysis relate to cognitive theories of human problem solving behavior? What are the links to other theories of monitoring? These types of questions cannot be answered without reference to some theoretical foundation that reveals similarities and differences in assumptions, objectives, and derivations.

The third limitation occurs when one tries to use the CSF technique as a foundation for further work. Without identifiable theory, extensions are difficult to construct. Without validation of the fundamental rule, upon which the technique rests, extensions are built upon an uncertain foundation.

Meaningful progress in our understanding of techniques to identify the monitoring information needs of senior managers can only be made from a firm foundation of established theory. Thus, there is a need for a fresh look at IRA for monitoring, from the perspective of established theory. It appears likely that such an effort would yield results related to CSF analysis, since the successful use of the technique is an indication of its substance. But a fresh look would go further. It would provide a technique that is testable. It would link to existing related theories, and it would provide a firm foundation
for further work.
3 MODELS OF THE VALUE OF MONITORING

3.1 Introduction

For a fresh look at information requirements analysis for monitoring, we will begin by examining the purpose of monitoring and the role of information in that process. There have been few attempts to describe in any detail the process by which managers use information to monitor situations. Aguilar (1967) provided an early study, but his focus was upon what managers monitored, rather than how they monitored. Mintzberg (1973), in his study of chief executive officer work, classified monitoring as one of ten major roles of the CEO. He provided great detail on the sources of information CEO's use, and in particular on the importance of informal sources of information, but again there were no results on the process managers used in monitoring. More recently, Kotter (1982) has developed a theory of how a manager's attention is allocated to different tasks. His concept of the managerial agenda again focuses upon understanding what managers do rather than how they do it.

The only detailed description of the process of monitoring was produced by Pounds (1969) more than a decade ago. His model of 'the process of problem finding' was developed after observing the work of "about fifty executives in a decentralized operating division of a large technically based corporation." [p. 4] The process model that Pounds developed was simple and nonmathematical. He wrote [p. 5]:
The word "problem" is associated with the difference between some existing situation and some desired situation. . . . the process of problem finding is the process of defining differences. Problem solving, on the other hand, is the process of selecting operators which will reduce differences. The member defines differences by comparing what he perceives to the output of a model which predicts the same variable.

According to Pounds, to find a problem, a manager needs two ingredients: understanding of the present condition of the situation and of how the situation should be. The latter serves as a point of reference for interpretation of the former. It is the size of the gap between these two ingredients that determines whether a problem exists.

Managers monitor situations so that they can keep informed. Keeping informed is apparently a worthwhile thing to do. Why? One reason is that it has intrinsic value. People like to be informed simply because it makes them feel better. But, in a managerial setting there is another, more powerful reason why managers monitor situations to keep informed. Monitoring often leads to managerial intervention to correct some problem or capitalize on some opportunity. It leads to action that can result in valuable outcomes. This is illustrated in Figure 3.1.

![Figure 3.1](image)

It is the value of these outcomes that makes monitoring a
worthwhile activity. For example, a manager monitors working capital levels in order to detect situations that require correction. A chief executive officer monitors competitors' moves so that he can alter company plans if the situation so dictates. In both cases, timely managerial action can have great positive value and that value is directly attributable to monitoring. Without monitoring, managers are not apprised of the need for intervention.

Information is the medium that connects the manager's monitoring efforts to the physical situations of interest. Just as objects are only observed through the light they reflect, so too managers observe situations only through information that results from those situations. Even when inventories are visually inspected, the information, visual in this instance, is the only medium that couples the physical goods with the manager's monitoring efforts. Figure 3.2 extends Figure 3.1 to illustrate the relationship between physical situations and outcomes, information, managerial monitoring, and managerial action.

The arrows in Figure 3.2 illustrate incomplete relationships. This is why broken arrows have been used. Each of these elements is not the only determinant of the next; there are many other external
factors not illustrated that influence the condition of situations, actions that are chosen, monitoring that is performed, and information that is monitored. For example, the condition of situations is influenced by chance events and other factors as well as by managerial action. Information contains noise and bias that is not a result of the physical situations and outcomes of interest. Planned actions may result from whim and desire as easily as from an assessment of information. And actual managerial action is not always the same as intended managerial action. A misread situation, or chance events that confound calculated action, will result in unintended consequences. In sum, Figure 3.2 illustrates an important, but incomplete set of elements of the monitoring system.

In determining information requirements for monitoring, one attempts to specify the best information to include in the monitoring system. But, 'best' can only be determined with reference to some objective, some standard for providing information. If the objective is to provide the most complete information on a situation, then best might translates into the most information. If the objective is to provide information that will yield the best management decisions, or the best outcomes for a manager, then the determination of best can be a complex task.

For many IRA techniques, the objective by which the suitability of information is measured is implicit in the technique. For example, many data analysis IRA techniques implicitly set an objective of providing the most complete and accurate representation of physical situations and outcomes. In terms of Figure 3.2, they focus upon the quality of the arc connecting physical situations and outcomes to
information. Other techniques focus upon providing management with information that satisfies their desires for information. The best information, in this case, is the information that management wants. This is a focus upon the arc connecting information to the management monitoring process.

Viewed in the context of the monitoring system illustrated in Figure 3.2, these two objectives for providing information for monitoring may not yield the desired results. The most complete and accurate information is not necessarily the most valuable information if it isn't used by the manager to monitor. The information that the manager wants may not be the most valuable, if the manager has not carefully thought through his information needs. Each of these objectives may be somewhat unsatisfactory because each considers only one part of the monitoring system. As Figure 3.2 illustrates, physical situations, information, monitoring, and actions jointly determine the outcomes that are of value to management. Each of the links between these elements should be considered in the determination of the best information to include in the monitoring system. In sum, the best information, the most valuable information to provide to managers for monitoring, is dependent upon the context in which it will be used.

To determine information requirements for monitoring, we will use a model of the value of information that includes consideration of such contextual variables as the characteristics of the monitored situations, how information is to be used by the manager to monitor, how monitoring results in actions, and the impact of those actions upon outcomes. For this, we turn to some simple mathematical models of the monitoring process as a guide to our intuition.
In this chapter we will review and reconstruct two models of the monitoring process derived from the accounting research literature. In the next chapter, these models will be analyzed, compared, and simplified to a form that will provide the basis for a new technique for IRA for monitoring.

3.2 The Mathematical Modeling Approach

The inherent qualities of any research approach bring strengths, limitations, and biases to a line of inquiry. For our study, we wish to build a simple model of the monitoring system that includes consideration of several elements and their relationships. Our interest is in finding an expression for the value of monitoring that can be used as a basis for a new technique for IRA. We will use mathematical modeling to guide our intuition in forming that model, both because it provides a set of powerful and flexible tools and because much detailed mathematical modeling of cost variance investigation, a type of monitoring, has already been done. The intention is not to derive new mathematical models of monitoring, because experience shows that these models are too detailed and often too complicated to be imbedded in an information requirements analysis technique. Instead, we will derive simple mathematical models of monitoring value for a range of assumptions and use them as a guide to intuition. In this section, we choose to examine the qualities of the mathematical modeling approach, so that we capitalize upon its strengths and attempt to compensate in our use of the medium, for its limitations.
Models of the managerial use of information for monitoring, attempt to mathematically describe aspects of human behavior. This task has two parts: the identification of important variables and the specification of the nature of the relationships between them. The selection of variables is guided by related research and intuition. We have identified situations, outcomes, information, managerial monitoring, and managerial actions as important variables. If others are missing, the model will fail as an adequate description. Unnecessary or less important variables will add complexity and degrade interpretability without sufficient offsetting benefits. The specification of relationships presents similar problems. Too simple a relationship will not adequately represent the interactive effects of variables, whereas overly complex relationships, although descriptively accurate, can inhibit the operationalization and utilization of the model in an applied information requirements analysis technique.

Ideally, one would like to produce models that are both sound, logical, and consistent and practical, applicable, and usable. The primary strength of mathematical modeling is that it is well suited to meeting the first set of requirements. It demands a precision of thought that goes well beyond the written word. Where one might write "a positive association", a mathematical translation would require specification of not just the direction, but also the form of the association. By keeping models simple, one can avoid many of these difficult specification problems. This may result in some inaccuracies in the models, but if the simplifications are powerful, these inaccuracies will be minor or related to unusual cases.
3.3 Models of Cost Variance Investigation

A classic example of monitoring activity is found in the control of production costs. This area has been studied in accounting for more than fifty years from the perspective of the manager who must decide whether to correct the state of some production process through his intervention. The value of intervention is directly related to the condition of the production process. If the manager chooses to intervene when the production process is in control, then he incurs a penalty. If he intervenes when the process is out of control, he makes a gain.

The branch of accounting research devoted to models of this monitoring process is usually known as the cost variance investigation literature. Its primary objective has been to provide policies based on cost information for when to intervene to correct a production process. Several types of rules have been proposed and analysed as to their economic consequences. An excellent review of research in this area is provided by Kaplan[1975]. In this section, we shall briefly review some of this work with an eye toward gaining intuition for a new technique for information requirements analysis for monitoring.

There are several ways to categorize the literature in this area. Kaplan uses a four cell scheme, differentiating policies by whether they consider a single or multiple production periods and whether or not the policy weighs the costs and benefits of intervention. We are focused upon these models for their ability to provide intuition as to how managers monitor situations. Therefore, an appropriate categorization for us is one that differentiates intervention policies.
by the manner in which cost information is processed. Three distinct information processing categories are evident in the literature. These we shall label the rules of thumb, the Bayesian, and the lens categories.

Rule of thumb intervention policies were the earliest and largest category of policies. They are based largely upon experience and intuition and provide simple rules for when to intervene. Usually, these rules do not balance the costs and benefits of intervention against each other. The two best known examples of rule of thumb policies are the Shewhart chart[1931] and Page's Cusum procedure.[1954] Both policies chart the deviation of production costs from some standard cost. In Shewhart's method, if the single period cost deviation is greater than one or two standard deviations, it indicates the need for correction of the production process. Thus, intervention is based upon the likelihood of the in control production process generating the observed cost information. If the likelihood is below some threshold, then intervention is mandated.

Page's method extends this technique by plotting the cumulative sum of multiple period cost deviations. If the production process is in control, then this sum should follow a random walk about the zero axis. Movement of the process out of control can be detected by a positive trend in the cusum plot. Page's method is more sophisticated than Shewhart's because it considers cost information generated over a number of production periods, but it is based upon the same principle. If there is a small likelihood that the in control production process generated the observed cost information, then intervention is deemed necessary.
A second category of intervention policies are those which use a Bayesian information processing approach to determine whether intervention is appropriate. Dyckman[1969] and Kaplan[1969] have provided models of production monitoring that weighs the costs and benefits of intervention for both single and multiple production periods. There are minor differences between these two models that have been discussed by Li[1970], but these have been found to have little practical significance.[Magee 1976] Both Dyckman and Kaplan have modeled the manager as a Bayesian information processor who each period monitors new information to form a judgement about the probability that the situation is out of control. Using this probability, he then weighs the relative expected value of intervention against the alternative of not intervening. If intervention is more valuable, the manager incurs an intervention cost, but corrects the situation if it was indeed out of control. This cycle of activity continues in each time period. The analyses of Dyckman and Kaplan derive the expected value of this monitoring activity as a function of characteristics of the situation, the available information, and the manager.

The third category of monitoring policies for production control use a simpler information processing algorithm, the lens model, to determine whether intervention is appropriate. Both the Bayesian and lens models of human information processing will be discussed in greater detail later in this chapter. Dittman and Prakash[1976] derive an optimal policy of the class that a manager chooses to intervene if the information signal, which represents a unit cost, exceeds some fixed critical level. In this case, the manager is assumed to pursue a fairly simple information processing strategy. In each period, he
reviews the information signal, decides whether it exceeds the critical level, and if it does, he intervenes to correct the situation if it indeed was out of control. Expected cost equations for this class of policies can be derived.

In these examples of cost variance investigation models, consideration of each element of the monitoring system is included. They are complex and sophisticated models for describing optimal monitoring policies under differing sets of assumptions. For us, they can provide a guide to intuition and a basis for developing a simple model of the value of monitoring a situation. We shall begin by developing detailed versions of the Dyckman, Kaplan, and Dittman and Prakash models from a common base of assumptions. This will allow us to compare the forms of the two models and to assess whether they imply different simplified models of monitoring value.

3.4 A Simple Framework for Models of the Monitoring System

In the rest of this chapter we will develop a single framework of assumptions and definitions that will allow the reconstruction of Dyckman's and Kaplan's Bayesian monitoring policy and of Dittman and Prakash's lens monitoring policy. This will facilitate direct comparison and analysis in the next chapter.

Let us begin by considering a single situation for monitoring. In a most parsimonious fashion, we may characterize the condition of the situation as being in one of two states, good or bad, in control or out of control, state 0 or state 1. We shall use the notation $s_0$ and $s_1$ to represent the two states, with $s_0$ being the generally preferred state.
which we shall call 'in control' and $s_1$ being the less preferred state, 'out of control'. State $s_1$ is less preferred because for each period the situation is in this state, the manager incurs a positive cost $C$. This cost is the difference in value to the manager between being in state $s_0$ and state $s_1$ for one period.

This characterization of the condition of the situation is, of course, much simpler than reality. There is more usually a continuum of states in which a situation can reside and a wide range of direct costs associated with being in the less than optimal state. For example, if the situation under consideration is a fast food establishment's reputation for prompt and efficient service, then good and bad provide only a gross characterization of the condition of the situation and the several bad situations that one might consider each have different associated costs. To describe this situation by only two states, the 'expected' or 'most likely' good condition and bad condition could be specified. The cost, $C$, could then be derived as the difference in value to the manager between being in these two states.

The two state characterization has been chosen here, and in the cost variance literature sighted in the previous section, because it simplifies the analysis. Whether it also damages the power of any resultant model is an empirical question. It, and questions of the validity of other simplifying assumptions will be partially addressed when our model of monitoring value is submitted to empirical test.

In each period, the manager has the opportunity to intervene to correct the situation if it is out of control. We will assume that if the manager chooses to intervene, then the situation will definitely be
in state \( s_0 \) just afterwards. That is, a manager can correct an out of control situation with certainty. In so doing, he has avoided the cost of being out of control, \( C \), which by convention is assessed just after the opportunity for intervention. But, the manager has incurred another cost. We will assume that there is a fixed positive cost \( K \) for intervention, whether or not the situation was originally in control. The cost to the manager of intervening is largely the opportunity cost of his time. If after intervention, the manager finds that the situation is out of control, then he returns it to the in control state. If he finds that the situation was actually in control, then he leaves it alone, but still incurs the opportunity cost of his time.

These assumptions have restricted our modeling in two important ways. First, it is assumed that a manager can always correct an out of control situation through intervention. This is not always true, especially when the out of control situation is beyond the manager's control. In this case, the assumption implies that the manager can adjust his plans to avoid the period cost, \( C \), for that situation being out of control. Even for situations directly within the control of the manager, it may not always be possible to completely correct them when they are out of control. Thus, this assumption may be a serious limitation of a model of monitoring value.

Nevertheless, the cost parameter \( C \) does represent a very meaningful aspect of a situation. The difference in value to the manager between being in control and out of control is a direct measure of the importance of that situation. Unimportant situations have small differences; it doesn't matter all that much whether they are in or out of control. Important situations have large \( C \) parameters. The
difference between being in or out of control is quite large.

The second important restriction of the model is that the costs of intervention and of leaving a situation out of control for a period do not vary over time. This is a reasonable restriction in the absence of knowledge to the contrary.

For convenience, we will refer to intervention as action \( a_1 \). The choice of not intervening is also an action, though a passive one. We shall refer to this as action \( a_0 \). The simple framework that has been discussed so far can be summarized in the following figure.

\[
\begin{array}{c|cc}
\text{s}_0 & \text{s}_1 \\
\hline
\text{in control} & \text{out of control} \\
\hline
a_0: \text{ don't intervene} & 0 & C \\
a_1: \text{ intervene} & K & K \\
\end{array}
\]

Cost of Each Action in Each State

Figure 3.3

If the situation is in control, in state \( s_0 \), then it is better to not act, to choose action \( a_0 \) than action \( a_1 \). Choosing to intervene when the situation is in control only results in a cost \( K \) for intervention. If the situation is out of control and the manager chooses action \( a_0 \), then the manager incurs a cost \( C \). If instead, action \( a_1 \) was chosen, then a cost \( K \) would be incurred. If the cost of intervention (\( K \)) was greater than the potential benefit of intervention (\( C \)), then the manager would never choose to intervene. Action \( a_0 \) would dominate action \( a_1 \), and monitoring would have no value, because the manager would always do best to ignore the condition of the situation and not intervene. Thus, to make this situation of interest to
monitor, we assume that \( C > K \).

If the condition of the situation did not change except through managerial intervention, then again it would be wholly uninteresting to monitor. Once it was in control it would remain there in perpetuity and could safely be ignored. Managers provide ongoing monitoring of situations because there is always some possibility that the situation will fall out of control.

In each period, we can distinguish two stages of the monitoring process. There is a state transition stage, in which there is some probability of change in the condition of the situation, and there is a control stage, in which the manager may intervene. The effect of the control stage upon the state of the situation has already been discussed. If the manager intervenes, then the state becomes \( s_0 \). If the manager chooses not to intervene, then the state of the situation remains unchanged. A similar representation is needed for the effect of the state transition stage. The two stage nature of each monitoring period is diagrammed in Figure 3.4.

---

**Figure 3.4**

Two Stages of Each Monitoring Period

A representation of the transition stage can be provided by a Markovian state transition matrix, which indicates the probability of moving from one state to the other. Let us represent by \( 1 - g \) the...
probability that a situation in state $s_0$ at the beginning of the period
remains in state $s_0$ at the end of the state transition stage (but
before control is exercised). It follows that $g$ is the probability
that the state will change to $s_1$. If the situation begins the period
in state $s_1$, then we will assume that it will be in state $s_1$ with
probability $h$ at the end of the state transition stage. This assumes
that the situation has a self correcting feature. If it falls out of
control then it may return to an in control state, without the
intervention of the manager, with probability $1-h$. The state
transition matrix is summarized in Figure 3.5.

<table>
<thead>
<tr>
<th>state after transition</th>
<th>$s_0$</th>
<th>$s_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>state $s_0$ before transition $s_1$</td>
<td>$g$</td>
<td>$1-g$</td>
</tr>
<tr>
<td></td>
<td>$1-h$</td>
<td>$h$</td>
</tr>
</tbody>
</table>

Markovian State Transition Matrix

Figure 3.5

The assumption that an out of control situation can return to an
in control state without managerial intervention reflects the reality
of management monitoring. It is a common assumption in the cost
variance investigation literature that a situation in an out of control
state can only return to control with managerial intervention ($h = 1$)
because a misadjusted machine has no self correcting feature. In a
managerial setting this may not be an accurate representation. Many
situations that managers monitor can correct themselves, either through
random events or through the intervention of others.

The Markovian state transition matrix is invariant from period to
period. Thus, we assume that the history of the situation can be summarized by its current state. No matter how long it has been since the last intervention, in each period a situation starting in state $s_0$ has an equal probability of falling out of control. That is not to say that the probability that a situation is out of control is unrelated to the number of periods since the last intervention, but only that in each period the transition probabilities are the same. This assumption has been made for three reasons. First, it is common in all the cost variance investigation literature. Second, it simplifies the analysis and finally an alternative formulation is not apparent.

The manager decides whether or not to intervene into the situation based upon his assessment of the condition of the situation. He begins each period with an initial assessment which he adjusts to reflect his knowledge about the state transition probabilities. We will represent the initial judgement of the probability that the situation is in state $s_1$ by $\pi$. It follows that $1-\pi$ is the manager's initial assessment of the probability that the situation is in state $s_0$. The manager's adjusted assessments of the probability of $s_1$ and $s_0$ will be represented by $p$ and $1-p$ respectively. $p$ is related to $\pi$, $h$, and $g$ in a fairly simple manner. The probability that the situation is in state $s_1$ at the end of the state transition stage is equal to the sum of the probability that it started in $s_0$ and changed to $s_1$ during the period and the probability that it started in $s_1$ and remained there during the period. That is,

$$p = (1 - \pi)(1 - g) + \pi h \tag{3.1}$$

$$1 - p = (1 - \pi)g + \pi(1 - h) \tag{3.2}$$
The last element of the monitoring system that needs to be described is the information system which the manager has available and uses each period to help decide whether to intervene. We will assume, in a most restrictive manner, that the information system that the manager has available has only two possible pieces of information, or signals. These signals we shall label \( y_0 \) and \( y_1 \).

The relationship between these information signals \( y_0 \) and \( y_1 \) and states \( s_0 \) and \( s_1 \) can be represented by conditional probabilities. The conditional probability of the manager obtaining signal \( y_0 \), given state \( s_0 \) shall be represented by \( r_0 \). Similarly, the probability of obtaining \( y_1 \), given \( s_1 \) will be represented by \( r_1 \). These definitions provide the following conditional probability matrix.

\[
\begin{array}{c|cc}
\text{signal} & s_0 & s_1 \\
\hline
y_0 & r_0 & 1 - r_1 \\
y_1 & 1 - r_0 & r_1 \\
\end{array}
\]

**Conditional Probabilities** \( p(y_i | s_j) \)

*Figure 3.6*

Without limitation, we can assume that:

\[ r_0 + r_1 > 1 \] (3.3)

This is not a limitation because if the opposite holds, then a simple relabeling of the information signals yields the above result. The assumption that there are only two information signals is a limitation made to simplify the analysis and interpretation of the model, but it does preserve some of the richness of the setting. In
general, the two signals could be thought of as a good signal and a bad signal. The probability of obtaining the good signal, $y_0$, is greater in state $s_0$ than it is in state $s_1$, since $r_0 > 1-r_1$. The opposite result holds for the bad signal, $y_1$, since $r_1 > 1-r_0$. $1-r_1$ and $1-r_0$ are measures of two types of error that the information system can produce. The first term is the probability of obtaining a good signal, given that the situation is actually out of control. This we shall call Type I error. The second term is the probability of obtaining a bad signal, given that the situation was in control. This is Type II error. $r_0$ and $r_1$ are indicators of the quality of the information system.

After the state transition stage the manager has formed an assessment of the probability that the situation is in state $s_1$. This we are representing by $p$. Information generated after the state transition stage is used to sharpen that assessment. Just before the manager decides whether to intervene, he uses specific information, generated after the state transition stage, to sharpen his judgement of the condition of the situation. These further refined judgements about the condition of the situation shall be represented by $p(s_0|y_1)$ and $p(s_1|y_1)$, where $y_1$ represents the specific information monitored by the manager. Of course, these two probabilities sum to one, so we need only be concerned with the determination of the latter.

Exactly how the specific information, $y_1$, is used to form the conditional probabilities is a matter of great debate. There are two competing paradigms of the utilization of information in judgement and choice, the Bayesian and the regression schools of thought. The essential difference between the two is in the manner of characterizing
the imperfect relationship between the information system and states of situations. The Bayesians propose the use of conditional probabilities to represent the relationship, while the regression school, formalized in the lens model proposed by Brunswik[1952, 1958], uses correlations of states with information signals. This fundamental difference results in two very different models for how information is used to assess the condition of a situation. After several hundred psychology studies of human judgement, the rivalry between the two schools remains intense, even though the differences are simple differences in assumptions. Despite obvious conceptual overlap, attempts at unifying the two views have met with limited success.[Slovic and Lichtenstein 1971] We shall examine each of these schools in turn.

3.5 The Bayesian Approach to Human Information Processing

Economics has adhered to the Bayesian view of information utilization ever since Savage[1947] first joined the concepts of utility and subjective probability into a formal, axiomatic theory of decision making. It provides a normative theory of information processing in the sense that Bayesian information processor makes the best and most complete use of information that is possible. Both Dyckman[1969] and Kaplan[1969] incorporate Bayesian views of information processing into their models of cost variance investigation. We shall present the Bayesian view of human information processing and next assess the descriptive validity of the treatment using the results of several experimental cognitive psychology studies.

The Bayesian approach to the determination of \( p(s_1|y_1) \) relies upon
the manager having knowledge of the probabilistic relationship between
the specific information signals and the different states of the
situation. This knowledge is in the form of conditional probabilities,
p(y_i|s_0) and p(y_i|s_1), the probabilities that one would obtain the
specific information signal, y, given that the situation is in one or
the other state.

With these probabilities and assessment of the probability that
the situation is in state s_1 made before viewing the information (p),
the manager can obtain p(s_1|y_i) by applying Bayes' rule.

\[
p(s_1|y_i) = \frac{p(y_i|s_1)p}{p(y_i|s_0)(1-p) + p(y_i|s_1)p} \quad (3.4)
\]

The expression for p(s_0|y_i) is similar to equation (3.4), except
with s_0 and s_1 reversed. When it is divided into (3.4), the following
alternative formulation of Bayes' rule is derived.

\[
p(s_1|y_i) = \frac{p(y_i|s_1)p}{p(s_0|y_i)p(y_i|s_0)1-p} \quad (3.5)
\]

In words, managers should form odds of being in s_1 versus s_0 equal
to the product of the likelihood ratio of y and the prior odds on s_1
and s_0. These formulae represent a normative model of the revision of
prior probabilities. There is no guesswork or testing as to whether it
is correct, for it can be derived from simple, accepted rules and
principles of probability theory. The formula describes how managers
should revise their prior assessment. But, does it also describe how
managers actually do it?

Early evidence was positive and optimistic. Peterson and
Beach [1968] reviewed early research on cognitive statistical ability and concluded:

Experiments that have compared human inferences with those of statistical man show that the normative model provides a good first approximation for a psychological theory of inference. Inferences made by subjects are influenced by appropriate variables in appropriate directions [p. 42-43].

Since that time, though, much of the evidence has not been supportive of the descriptive validity of the Bayesian model of human information processing. Slovic and Lichtenstein [1971] reviewed more than 75 papers that empirically tested the descriptive capabilities of the Bayesian model. They wrote:

The primary finding has been labeled conservatism: Upon receipt of new information, subjects revise their posterior probability estimates in the same direction as the optimal model, but the revision is typically too small; subjects act as if the data are less diagnostic than they truly are. Subjects in some studies have been found to require from two to nine data observations to revise their opinions as much as Bayes' theorem would prescribe for one observation. [p. 693]

Conservatism is the systematic underutilization of information signals. With reference to equation (3.5), it is underemphasis of the first multiplicative ratio, $p(y_i|s_1)/p(y_i|s_0)$, in favor of the prior odds of $s_1$ versus $s_0$. Most of the papers that Slovic and Lichtenstein cited were explorations of causes of the conservatism finding. The authors clustered the varied explanations into three categories: misperception, misaggregation, and artifact. Both misperception and misaggregation are problems relevant to our modeling effort at hand.

Misperception in this context refers to a subject's difficulty in estimating $p(y_i|s_0)$ or $p(y_i|s_1)$. The problem is apparent even in experimental settings where these distributions are readily
calculatable without error. For example, in a typical experiment subjects are asked to estimate the probability that a randomly drawn red marble came from an urn containing ninety red marbles and ten white marbles, rather than from an urn containing red and white marbles in opposite proportion. In this case, $p(y_1|s_0)$ and $p(y_1|s_1)$ are simply 0.9 and 0.1, yet evidence indicates subjects' difficulties in determining these probabilities. For more complex information signals, the misperception problem may be even worse. Cohen, Chesnick, and Hanan[1972], Bar-Hillel[1973], and Wyer[1970] provide evidence that man has great difficulty in correctly perceiving or estimating the probability of compound information signals. Thus, misperception of the probabilities of receiving an information signal may significantly impair the descriptive validity of the Bayesian model.

The misaggregation problem refers to the inability of subjects to correctly aggregate probability information using Bayes' rule. Kahneman and Tversky[1972, 1973] have produced compelling evidence that in estimating probabilities subjects often overutilize information signals, rather than revise prior probabilities conservatively. In one simple experiment, they provided subjects with a description of a room populated with a certain proportion of engineers versus lawyers and a description of a specific individual. The subjects were asked to estimate the probability that the individual was a lawyer and it was found that this estimate was almost entirely insensitive to the proportion of engineers and lawyers in the room. In the absence of specific information about the individual, subjects correctly used the prior estimates, the proportion of engineers and lawyers, to assess the likelihood that the individual was a lawyer. Yet, when other
information was introduced, prior information was largely ignored. In
Kahneman and Tversky's words, "The failure to appreciate the relevance
of prior probability in the presence of specific evidence is perhaps
one of the most significant departures of intuition from the normative
time of prediction."[1973, p. 243] They conclude that "in his
evaluation of evidence, man is apparently not a conservative Bayesian:
he is not Bayesian as all."

This represents perhaps the most pessimistic assessment of the
descriptive validity of the Bayesian model of information processing.
More sympathetic views are held by some who observe that Bayesian
information processing makes the best and most complete use of
available information and this is what man strives to do. In specific
circumstances he may err, but in general the model provides a fairly
accurate description. It would be imprudent not to explore a model of
the monitoring system based upon an assumption that the manager is a
Bayesian information processor. But, there is a competing view of
human information processing. This should also be explored.

3.6 A Bayesian Model of the Monitoring System

To determine the value of monitoring we must construct a model of
the expected cost with monitoring and another of the expected cost
without monitoring. These we shall designate as EC(M) and EC(O),
respectively. The difference between these two is the value of
monitoring. In any period, the manager can receive information signal
Y_0 with a probability that we will denote by p(Y_0) and information
signal Y_1 with probability p(Y_1).
Let us represent by $E(a_i | y_j)$ the expected cost to the manager of choosing action $a_i$ given that he observed information signal $y_j$. The manager will use the information signal $y_j$ to assess $E(a_0 | y_j)$ and $E(a_1 | y_j)$ and will choose the action which has the lower expected cost. Then, the expected period cost with monitoring, $EC(M)$, is given by:

$$EC(M) = p(y_0) \cdot \min\{E(a_0 | y_0), E(a_1 | y_0)\} + p(y_1) \cdot \min\{E(a_0 | y_1), E(a_1 | y_1)\}$$

(3.6)

The manager assesses the expected costs of different actions with reference to the costs of intervening and of not intervening. These costs are contained in Figure 3.3.

$$E(a_0 | y_0) = 0 \cdot p(s_0 | y_0) + C \cdot p(s_1 | y_0)$$

(3.7)

$$E(a_1 | y_0) = K \cdot p(s_0 | y_0) + K \cdot p(s_1 | y_0) = K$$

(3.8)

$$E(a_0 | y_1) = 0 \cdot p(s_0 | y_1) + C \cdot p(s_1 | y_1)$$

(3.9)

$$E(a_1 | y_1) = K \cdot p(s_0 | y_1) + K \cdot p(s_1 | y_1) = K$$

(3.10)

Substituting these equations into equation (3.6) yields:

$$EC(M) = p(y_0) \cdot \min\{C \cdot p(s_1 | y_0), K\} + p(y_1) \cdot \min\{C \cdot p(s_1 | y_1), K\}$$

(3.11)

If the manager did not use information to monitor the situation, then he would use the probabilities $p$ and $1-p$ to assess whether intervention was worthwhile. If the manager chooses not to intervene, then he can expect a cost $C \cdot p$. If the manager intervenes, then the cost is $K$. He chooses his action to minimize cost. Therefore, the expected cost without monitoring, $EC(0)$, is given by:

$$EC(0) = \min\{C \cdot p, K\}$$

(3.12)

The value of monitoring is equal to the expected value of outcomes
with monitoring minus the expected value of outcomes without monitoring. It is equal to the value of improved decision making brought about through superior information. In our framework, the value of monitoring has been represented by the following formula.

\[ \text{VM} = \text{EC}(0) - \text{EC}(k) \]

\[ = \min[C \cdot p, k] - p(y_0) \cdot \min[C \cdot p(s_1 | y_0), k] \]

\[ - p(y_1) \cdot \min[C \cdot p(s_1 | y_1), k] \]  (3.14)

The minimization functions reflect the fact that a manager will choose from among the two available actions that which minimizes his period cost. Without information, this is a simple matter of determining whether the expected cost of not intervening, \( C \cdot p \), is less than the intervention cost, \( k \). When information is used, these expectations are determined using the revised state probabilities, \( p(s_1 | y_0) \) and \( p(s_1 | y_1) \). In this section, we will assume that these revisions are made by the manager in a Bayesian fashion.

Before the manager receives information signal \( y_0 \) or \( y_1 \), he has a prior assessment of the probability that the situation is out of control. This we are representing by \( p \). As we have seen, this prior probability is related to initial judgements about the state of the situation and to the probabilities of the situation changing states through equation (3.1). In this section, we have assumed that the manager uses information signals in a Bayesian fashion. Thus, the prior assessment, \( p \), is also related through Bayes formula to the manager's final assessment of the probability that the situation is out of control. We have that:

\[ p(s_1 | y_0) = \frac{p(y_0 | s_1) \cdot p}{p(y_0)} \]  (3.15)
These two equations, together with equation (3.1), summarize how a Bayesian manager assesses the probability that the situation is in need of intervention. They may be substituted in the value of monitoring model, equation (3.14), to yield a model of the value of monitoring to a Bayesian information processor.

$$VM = \min[C*p,K] - \min[C*(1-r_1)*p,K*{r_0*(1-p)+(1-r_1)*p}]$$

$$- \min[C*r_1*p,K*{(1-r_0)*(1-p)+r_1*p}]$$

(3.19)

To better understand this equation, let us explore it in two regions, for $C*p<K$ and for $C*p>K$. If $C*p<K$, then the expected cost of intervention, $K$, exceeds the expected cost of nonintervention. Thus, without other information the manager would choose not to intervene. If $C*p<K$, then the model of the value of monitoring reduces to:

$$VM = C*p - \min[C*(1-r_1)*p,K*{r_0*(1-p)+(1-r_1)*p}]$$

$$- \min[C*r_1*p,K*{(1-r_0)*(1-p)+r_1*p}]$$

(3.20)

Also, from equation (3.3) we have that:

$$1-r_1 < r_0$$

(3.21)

$$(1-r_1)*(1-p) < r_0*(1-p)$$

(3.22)
\[1 - r_1 < r_0 * (1-p) + (1-r_1) * p \quad (3.23)\]
\[C * (1-r_1) * p < K * \{r_0^* (1-p) + (1-r_1) * p\} \quad (3.24)\]
\[\min[C*(1-r_1)*p, K\{r_0^*(1-p)+(1-r_1)*p\}] = C*(1-r_1)*p \quad (3.25)\]

The model for the value of monitoring reduces to:

\[V_M = C*p - C*(1-r_1)*p - \min[C*r_1*p, K\{(1-r_0)*(1-p)+r_1*p\}] \quad (3.26)\]
\[= C*r_1*p - \min[C*r_1*p, K\{(1-r_0)*(1-p)+r_1*p\}] \quad (3.27)\]
\[= \max[0, (C-K)*r_1*p-K*(1-r_0)*(1-p)] \quad (3.28)\]

The above value of monitoring model applies when \(C*p<K\), that is, when without monitoring the manager would choose not to intervene. If the information monitored by the manager reinforces the case against intervention, if it reduces further the expected cost of nonintervention, then the manager wouldn't change his actions and there wouldn't be any change in the state of the situation. But, if the manager monitors a bad signal, \(y_1\), he will revise upward his estimate of the probability that the situation is out of control and this will decrease the expected advantage of nonintervention over intervention. But, the manager will not necessarily choose to intervene when \(y_1\) is observed.

To see this, let us examine the above value of monitoring model. The first term of the maximization in equation (3.28) is zero. This represents the expected value of receiving information signal \(y_1\) and not intervening. If no intervention is contemplated, then no value is expected. The second term of the maximization represents the expected value of receiving information signal \(y_1\) and intervening. With probability \(r_1*p\) the manager will correctly intervene when the
situation is out of control and benefit by an amount (C-K). With probability \((1-r_0)*(1-p)\) the manager will incorrectly intervene when the situation is in control and incur a cost \(K\). The value of monitoring in this instance is the difference between these expected benefits and costs. Intervention upon observation of \(y_1\) can have a negative expected value if the expected cost of incorrectly intervening outweighs the expected benefit of correctly intervening. Thus, even after observing \(y_1\), the manager may still choose not to intervene. Then, according to intuition and to the formula, monitoring has zero value, since it cannot result in any change in expected outcomes. But, it is more usual that monitored information can affect the actions that are chosen by a manager. In this case, monitoring has a positive expected value.

Now let us consider the second case, where \(C*p>K\). If \(C*p>K\), then the expected cost of intervention, \(K\), is less than the expected cost of nonintervention. Thus, without other information the manager would always choose to intervene. If \(C*p>K\), then the model of the value of monitoring reduces to:

\[
VM = K - \min[C*(1-r_i)*p,K*\{r_0*(1-p)+(1-r_i)*p\}]
- \min[C*r_i*p,K*\{(1-r_0)*(1-p)+r_i*p\}] \tag{3.29}
\]

Also, from equation (3.3) we have that:

\[
r_i > 1-r_0 \tag{3.30}
\]
\[
r_i *(1-p) > (1-r_0)*(1-p) \tag{3.31}
\]
\[
r_i > (1-r_0)*(1-p) + r_i*p \tag{3.32}
\]
\[
C*r_i*p > K*\{(1-r_0)*(1-p)+r_i*p\} \tag{3.33}
\]
\[
\min[C*r_i*p,K*\{(1-r_0)*(1-p)+r_i*p\} = K*\{(1-r_0)*(1-p)+r_i*p\} \tag{3.34}
\]
The equation for the value of monitoring reduces to:

\[ VM = K - \min[C(1-r_1)p, K\{r_0(1-p) + (1-r_1)p\}] \]
\[- K\{(1-r_0)(1-p)+r_1p\} \]  

(3.35)

\[ = K\{r_0(1-p) + (1-r_1)p\} \]
\[- \min[C(1-r_1)p, K\{r_0(1-p) + (1-r_1)p\}] \]  

(3.36)

\[ = \max[0, K\{r_0(1-p) - (C-K)(1-r_1)p\}] \]  

(3.37)

The above model is similar in form to that derived for the case when the alternative to monitoring was nonintervention, when \(C*p<K\). Here we have the model for the opposite condition, when intervention is chosen in the absence of monitoring, and analogous but opposite interpretations of the model apply. The base case is that the manager will intervene. If even upon receipt of the good information signal the manager would still choose to intervene, then monitoring has zero value. But, if the expected savings associated with reduced intervention outweigh the expected penalty of being incorrect, then there is value to intervening upon receipt of \(y_0\), and monitoring has a positive expected value.

Equations (3.28) and (3.37) are a piecewise restatement of the model in equation (3.19). They offer a more interpretable form that will be explored in the next chapter.

\[
VM = \begin{cases} 
\max[0, (C-K)r_1p-K(1-r_0)(1-p)] & C*p<K \\\n\max[0, K\{r_0(1-p) - (C-K)(1-r_1)p\}] & C*p>K
\end{cases}
\]  

(3.38)

The above model of monitoring value has only considered the
actions of a manager for a single period in time. How can this model be extended to a multiperiod model? The simple answer is that this can be accomplished by subscripting each term in equation (3.38) with an 'n'.

\[
V_{M_n} = \begin{cases} 
\max \{0, (C_n - K_n) \times r_1 \times p_n - K_n \times (1 - r_0) \times (1 - p_n)\} & C_n \times p_n < K_n \\
\max \{0, K_n \times r_0 \times (1 - p_n) - (C_n - K_n) \times (1 - r_1) \times p_n\} & C_n \times p_n > K_n 
\end{cases} 
\]

(3.39)

Indeed, this is a correct answer, but one that requires careful interpretation. The term \( p_n \) now represents the prior probability that the situation is out of control in period \( n \), just as in a single period model. Adjustments in this probability from period to period are made in standard Bayesian fashion. The terms \( C_n \) and \( K_n \) are more difficult to interpret. Duvall (1967) and Dyckman (1969) observe that it is difficult to determine precisely the future cost savings associated with immediate intervention because of uncertainty as to how long the situation will stay in control. Dyckman suggests that \( C_n \) can be approximated by a constant equal to the single period savings, \( C \), times the expected number of periods that the situation will stay in control. (1969, p. 218) Kaplan (1969) uses a more sophisticated approach, dynamic programming, to obtain precise values for \( C_n \) and \( K_n \). His results are theoretically optimal, but in practical terms they are little different that Dyckman's. Magee, in a comparative empirical study of the Dyckman and Kaplan models concludes, "... criticism of Dyckman's [1969] approach for not considering future actions, while valid theoretically, may have little effect on the incremental cost savings, at least in the cases examined." (1976, p. 537)

This is an important result. Dyckman suggests that coefficients
Cₙ and Kₙ may be given constant values for all periods. What this does is allow us to model multiperiod monitoring as a series of single period decisions, linked only by the manager's Bayesian revision of pₙ.

3.7 The Lens Model of Human Information Processing

Simon has observed:

... a great deal can be learned about rational decision making by taking into account, at the outset, the limitations upon the capacities and complexity of the organism, and by taking account of the fact that the environments to which it must adapt possess properties that permit further simplification of its choice mechanisms.

A simplified model of human information processing has been presented by Egon Brunswik, who studied people's abilities to adapt to turbulence in their environment. At the center of his work was a model of an individual's use of information to predict the state of his environment. It is analogous to our interest in modeling a manager as he monitors the condition of a situation.

Brunswik developed his model of individual use of information for purposes of studying adaptability to environmental turbulence. In a typical experiment a subject would be provided with three sources of information (y₁, y₂, y₃), each providing as data, a number between zero and one hundred. The subject would be asked to predict a fourth number, (P), on the basis of the three imperfect linear predictor sources provided. After the subject makes his judgement, the actual fourth number, (A), is shown and the treatment is repeated. (See Figure 3.7). As the subject learns the relationships between each information source and the fourth number, A, his judgement becomes more
accurate. The quality of learning that occurs can be measured by comparing the squared correlation of the series A and P, ($R^2_{ap}$) with the coefficient of determination of the regression of the three information sources on the series A, $R^2_{3a}$. This coefficient provides an upper bound on the accuracy of the subject's predictions. The best he could expect is to use the linear predictors in the correct proportions, such that

$$R_{ap} = R_{1a}.$$

The Lens Model of Human Information Processing

**Figure 3.7**

Brunswik studied subjects' adaptability to environmental turbulence in two ways. First, he held constant the correlations between information sources and the series A ($r_{1a}$, $r_{2a}$, $r_{3a}$), but increased the variance of the information source values. The subjects would have to adapt to a wider range of predictor values. A second
type of turbulence could be introduced by varying the relationship between information sources and the series A. This would require the subjects to adapt to a new pattern of use of the information sources, to alter the utilization coefficients $r_{1p}$, $r_{2p}$, and $r_{3p}$.

The primary use of the Brunswik lens model in the last ten years has been as a model of how individuals utilize information in judgement and choice. This was not the intended purpose of the model. It was put forth as a measurement model that allowed Brunswik to quantify important learning phenomena, not as a description of an actual cognitive process. Nevertheless, many researchers have found it to be a satisfactory descriptive model, as well. Dudycha and Naylor[1966] provided perhaps the first adaption of Brunswik's lens model specifically to the human information processing realm. The primary attraction of the model is its simplicity as compared with the Bayesian model of information processing. The model assumes that all that is known or learned about the relationship between an information source and a situation of interest can be summarized by a correlation coefficient. It also has appeal because information use is modeled as a linear process, simple in form and naturally learnable.

In their review of information processing in judgement, Slovic and Lichtenstein[1971] referenced more than one hundred papers that have used the lens model to study information source utilization when the sources were linear or nonlinear, independent or intercorrelated, consistent or variable, and ranging in number and format. The conclusions from this review are nicely summarized by Slovic, Fischhoff, and Lichtenstein[1977, p.13]

They concluded that: (a) subjects can learn to use linear cues appropriately; (b) learning of nonlinear
functions is slow, and especially when subjects are not forewarned that relations may be nonlinear; (c) subjects are inconsistent, particularly when task predictability is low; (d) subjects fail to take proper account of cue intercorrelations; and (e) outcome feedback is not very helpful.

Research during the past half decade has confirmed and extended these conclusions.

Libby and Lewis[1977] reviewed eleven lens model studies in the accounting area, all but one conducted after the Slovic and Lichtenstein review. The subjects' tasks in these experiments included recommending of stocks for investment, planning audit workloads, and predicting bankruptcies and stock price changes. The conclusions that may be drawn from these studies are consistent with the Slovic and Lichtenstein summary. Individuals generally utilize information sources in a highly linear manner and are quite accurate in their predictions, but there was little consensus among individuals about the relative importance of various information sources. Subjects varied greatly in their use of information. Nevertheless, they were consistent in the accuracy of their predictions.

These studies provide some confirmatory evidence for the fundamental assumption that information is used in a linear fashion. This is the basis for the lens model of human information processing. This model is very different from the Bayesian model, which indicates that information is utilized in a nonlinear way. Attempts have been made to integrate the two views [Mock and Vasarhelyi 1978; Hilton 1980], but these have not been altogether successful.

Just how managers do utilize information for monitoring is an important concern for modeling the monitoring system. We have available two alternatives, each of which has its strengths and
weaknesses. On the foundation of assumptions and definitions already prepared we have built the Bayesian model of the monitoring system. In the next section, a lens model of monitoring will be constructed. A comparison of these models will provide some indication of the sensitivity of results to the choice of information processing model.

3.8 A Lens Model of the Monitoring System

The lens model of human information processing provides an alternative view of how managers use information to decide whether a situation warrants intervention. It assumes that managers make direct estimates of the state of the situation, not of the likelihood of the situation being in one state or another. These direct estimates are made by using available information linearly. Prior probabilities and conditional probabilities are not relevant to this simple model. On the basis of his estimate of the state of the situation, the manager decides whether intervention is appropriate.

In our framework, the situation can be in only one of two states. Thus, estimation of the state of the situation can have only two results, $s_0$ or $s_1$. This simplifies greatly the lens model of monitoring. If the manager receives information signal $y_0$, then the indication is that the situation is in control. Thus, the estimate of the state will be $s_0$ and on the basis of this, the manager will choose not to intervene. If information signal $y_1$ is received, then the indication is that the situation is out of control. In this case, the estimate of the situation's state is $s_1$ and the manager will conclude that it is best to intervene. The lens model of human information
processing results in a model of managerial monitoring that is the same as a single period control limit policy for monitoring. If the information signal is $y_0$, choose $a_0$; if it is $y_1$, choose $a_1$.

With this understanding of the monitoring behavior of the manager, we can construct a formula for the expected period cost with monitoring. With probability $p(y_0)$ the manager will receive information signal $y_0$ and choose action $a_0$. In this case his cost will be $E(a_0|y_0)$. The rest of the time, the manager will receive information signal $y_1$, choose action $a_1$, and incur cost $E(a_1|y_1)$.

Thus, we have that:

$$EC(M) = E(a_0|y_0)*p(y_0) + E(a_1|y_1)*p(y_1)$$

(3.40)

Equations (3.7) and (3.10) provide simpler equalities for the two expected costs in equation (3.40). When these are substituted into equation (3.40), the following alternate form is obtained.

$$EC(M) = C*p(s_1|y_0)*p(y_0) + K*p(y_1)$$

$$= C*p(y_0|s_1)*p(s_1) + K*[p(y_1|s_0)*p(s_0)+p(y_1|s_1)*p(s_1)]$$

(3.42)

$$= C*(1-r_1)*p + K*{(1-r_0)*(1-p)+r_1*p}$$

(3.43)

The expected cost without monitoring remains unchanged. It is unaffected by the information processing approach used by the manager.

$$EC(0) = \min[C*p,K]$$

(3.44)

From (3.43) and (3.44), we can obtain a model of the value of monitoring for a manager who processes information in a lens model fashion.

$$VM = \min[C*p,K] - C*(1-r_1)*p - K*{(1-r_0)*(1-p)+r_1*p}$$

(3.45)
The lens model uses only new information in determining whether intervention is appropriate. If signal \( y_1 \) is received, intervention is chosen. Otherwise, the manager will choose not to intervene. Prior information, efficiently summarized by \( p \), the prior probability that the situation is out of control, isn't used to decide whether to intervene. Prior information does have an important role, though, in determining a value for such monitoring activity. That is why it is part of equation (3.46).

The above model for the value of monitoring can assume negative values. That is, through monitoring activities that use information signals in a lens fashion, the manager can actually be worse off than if he did no monitoring at all. For example, it may be that previous information signals and interventions point overwhelmingly toward one action or another, but that the new information signal, which determines actions, indicates otherwise. In this case, monitoring has a negative expected value.

The Bayesian model of the expected value of monitoring is quite similar to the lens model of monitoring value. In the Bayesian model, equation (3.38), prior information is used efficiently and the value of monitoring can never be negative. Comparison of equations (3.38) and (3.46) shows that this is the only difference between the models. It is not surprising that the two models of human information processing lead to strikingly similar models of the value of monitoring. At the level of aggregation of these models, differences between the two
information processing schools are difficult to detect.

Like equation (3.38), the above model of the value of monitoring considers only a single period of monitoring. If we move to a multiple period model, it is possible to compute the steady state probability that the situation is out of control, $p^s$. This can be used in equation (3.46) to determine the value of monitoring at steady state.

In the framework we have been using, two stages of a monitoring period have been described: the transition stage and the control stage. The transition stage is where the state of the situation can change due to external influences. The transition matrix describing the probability of different changes is shown in Figure 3.5. A similar matrix exists for the control stage. The control matrix describes the probability of ending the period in either state, given that one began the control stage in either state.

$$\begin{array}{c|cc}
\text{state after control} & s_0 & s_1 \\
\text{state} & s_0 & 1 & 0 \\
\text{before} & s_1 & r_1 & 1-r_1 \\
\text{control} & s_1 & & \\
\end{array}$$

Markovian State Control Matrix

Figure 3.8

If one begins the control stage in state $s_0$, in control, then no matter whether the manager intervenes or not, the situation will be in state $s_0$ at the end of the period. If the control stage begins with the situation in state $s_1$, then the state at the end of the period depends upon whether the manager intervenes to move the situation to state $s_0$. He will do so if he receives information signal $y_1$. The probability of this, given state $s_1$, is $r_1$. Thus, the probability of
starting and ending the control stage in state $s_1$ is $1 - r_1$.

The product of the transition matrix and the control matrix is a matrix describing the probability of being in one or the other state at the beginning and end of the entire monitoring period. This is shown in Figure 3.9 and will be referred to as the transition and control matrix, to indicate that it covers both stages.

\[
\begin{array}{ccc}
\text{state before} & s_0 & s_1 \\
\text{transition and control} & & \\
\text{state after} & & \\
\end{array}
\]

\[
\begin{array}{ccc}
\text{transition} & r_1 + g^* (1 - r_1) & 0 \\
\text{and control} & 1 - h^* (1 - r_1) & h^* (1 - r_1) \\
\end{array}
\]

Markovian Transition and Control Matrix

Figure 3.9

From the transition and control matrix, we can compute the steady state initial probability, $\pi^S$, and use equation (3.1) to compute $p^S$. At steady state, the initial probability $\pi^S$ is equal for all periods. Thus, $\pi^S$ remains unchanged after applying the transition and control matrix, since the result is the initial probability for the next period. Thus, we have that:

\[
\pi^S = (1 - \pi^S)(1 - g)(1 - r_1) + \pi^S h^* (1 - r_1)
\]

\[
\pi^S = \frac{(1 - g)(1 - r_1)}{1 - (g + h - 1)(1 - r_1)}
\]

Applying equation (3.1) allows us to determine the final formula for $p^S$. This can be substituted into equation (3.46) to provide a model of the expected value of monitoring at steady state.
\[ p^S = (1-p^S)(1-g) + p^S h \] (4.49)

\[ \frac{(1-g)}{1 - (g+h-1)(1-R)} \] (4.50)

### 3.9 Conclusions

Monitoring is the use of information to more accurately assess the condition of a situation, so that intervention decisions can be more accurately made. Monitoring has value because it can result in economically more efficient maintenance of the situation. It was observed in this chapter that there are four elements to any monitoring system: a situation of economic interest, information about the state of the situation, a manager who monitors the situation by observing the information, and a choice of actions that can change the condition of the situation.

Accounting models of cost variance investigation include consideration of all these elements. Although these models are specialized to the study of policies for the investigation of production cost overruns, they exhibit the features of a general monitoring system. Upon a common base of definitions and assumptions the two leading cost variance investigation models were reconstructed as a guide to our intuition. One model assumed that the manager used a Bayesian information processing strategy while the other assumed a lens information processing strategy. The result of these reconstructions was two models of the value of monitoring a situation. These two models were strikingly similar, bearing evidence that at the present
level of aggregation, differences in human information processing styles are not materially important. This is an important result for our attempt to provide a new technique for information requirements analysis for monitoring. At the center of that new technique will be a set of variables that determine the value of monitoring. If different assumptions about human information processing result in very different models of the value of monitoring, then we would be uncertain about which variables to include in our new technique.

We now have the functional form of a model of the value of monitoring. Imbedded in a technique, this model could allow a manager to determine which situations are most valuable to monitor. This can be a crucial step in determining information requirements for monitoring, for once a situation has been chosen for monitoring, it is usually a relatively easy task to determine which specific data are appropriate.

There is some evidence that information models at the level of detail of equations (3.38) and (3.46) are quite difficult to implement or to test. For example, Uecker [1978, 1980] tested whether subjects chose the most valuable information system, as determined by a model of information value. The results were negative because there were difficulties with the test. Hilton, et al [1981] and Hilton and Swieringa [1981] tested subjects perceptions of the relationship between information value and information quality, using a model of information value. The two tests came to opposite conclusions because of problems with the test. Schepanski and Uecker [1983] observed these test difficulties and performed a carefully constructed experiment to test a model of information value. They concluded:
Previous research has raised doubts about the appropriateness of normative models of information evaluation as positive models of information-evaluator behavior. The present experiment provides strong confirmation of those doubts. One response to this confirmation is to attempt to modify normative models to account for the observed discrepancies. An alternative approach, which we illustrate, is to identify other theoretical models which are capable of providing parsimonious representation of the observed behavior.[p. 280]

The Schepanski and Uecker study provides a caution to our analysis. In the next chapter, we will analyze our models of the value of monitoring to see if they can guide us toward an intuitive and testable model of the value of monitoring.
4.1 Introduction

In the last chapter, two models of the value of monitoring were derived from a common base of definitions and assumptions. One model assumed that the manager was a Bayesian information processor while the other assumed that he pursued a lens information processing strategy. The two models are shown below as equations (4.1) and (4.2) respectively.

\[
V_M = \begin{cases} 
\max(0, (C-K)r_1p-K(1-r_0)(1-p)) & \text{if } C*p<K \\
\max(0, K(1-p)-(C-K)(1-r_1)p) & \text{if } C*p>K 
\end{cases} \tag{4.1}
\]

\[
V_M = \begin{cases} 
(C-K)r_1p - K(1-r_0)(1-p) & \text{if } C*p<K \\
K(1-p) - (C-K)(1-r_1)p & \text{if } C*p>K 
\end{cases} \tag{4.2}
\]

One can observe that the two models are remarkably similar. They differ only at the extreme values of p, the prior probability that the situation under scrutiny is out of control. This can be seen easily when the two equations are plotted, as in Figure 4.1.
It is an empirical question as to whether the differences between these two models are significant. On balance, we would expect that for a large range of values of \( p \), the value of monitoring would be positive. Thus, from an empirical perspective, the two models would not exhibit significant differences. To avoid having to deal with the discontinuities at the extremes of equation (4.1), we will continue the analysis using equation (4.2) as the model of the value of monitoring. Of course, the modeling results that will be derived apply equally to the nonzero portion of equation (4.1) and it is expected that the results will be empirically valid for whichever information processing strategy is used by the manager.

Itami has identified four factors that are the critical determinants of information value. \cite{Itami, 1977} Three of these are evident in the value of monitoring model: an information structure,
represented by the terms \( r_0 \) and \( r_1 \), uncertainty about the condition of the situation, represented by \( p \), and an economic cost structure, represented by \( C \) and \( K \). The fourth element, the structure of the action set, is not evident because of the restricted nature of monitoring and of our framework.

The information structure is represented by the conditional probabilities of receiving either of two information signals, given that the situation is in one or the other state. These probabilities are shown in Figure 4.2. We have been able to assume that \( r_0 \) and \( r_1 \) sum to at least one, since if they did not, it could be achieved by a simple relabeling of information signals \( y_0 \) and \( y_1 \).

\[
\begin{array}{c|cc}
\text{state} & s_0 & s_1 \\
\hline
\text{signal} & y_0 & r_0 & 1 - r_1 \\
& y_1 & 1 - r_0 & r_1 \\
\end{array}
\]

Conditional Probabilities \( p(y_i | s_j) \)

Figure 4.2

Uncertainty about the condition of the situation derives from the possibility that in any period the situation can randomly move from one state to the other. The manager's uncertainty about the state of the situation is summarized by the term \( p \), the probability that the situation is out of control.

If the manager chooses to intervene, he is assured of a cost \( K \) of intervention and only a cost \( K \), since if he finds the situation out of control he can correct it before an out of control cost \( C \) is incurred. If the manager does not intervene, he risks the cost \( C \) if the situation
is out of control; otherwise, the cost is zero. This structure to the economic consequences of the manager's intervention is summarized in Figure 4.3.

<table>
<thead>
<tr>
<th></th>
<th>$s_0$</th>
<th>$s_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>in control</td>
<td>out of control</td>
</tr>
<tr>
<td>$a_0$: don't intervene</td>
<td>0</td>
<td>C</td>
</tr>
<tr>
<td>$a_1$: intervene</td>
<td>K</td>
<td>K</td>
</tr>
</tbody>
</table>

Cost of Each Action in Each State

Figure 4.3

These three elements, an information structure, uncertainty about the condition of the situation, and an economic cost structure, are the determinants of the value of monitoring. In the next three sections of this chapter, each of these elements will be analyzed for the purpose of developing a set of testable hypotheses about the value of monitoring.

4.2 The Effect of Information Quality Upon Monitoring Value

The conditional probabilities $r_0$ and $r_1$ are measures of the quality of the information system employed for monitoring. A perfect information system is one in which $r_0$ and $r_1$ both equal one. In this case, there is an exact relationship between information signal and state. If $y_0$ is received, then the state must be $s_0$; if $y_1$ is received, the state is $s_1$. The least useful information system is one where $r_0$ and $r_1$ are both equal to one half. In this case an information signal is just as likely to have resulted from either
state. Thus, the signal provides no indication about which state the situation is in. Most information systems are found somewhere between these extremes. They provide imperfect, but useful information about the state of the situation.

Equation (4.2) can be reformatted to more clearly indicate the relationship between measures of information system quality and monitoring value. The result is shown in equation (4.3).

\[
VM = \begin{cases} 
  r_1 \ast (C-K) \ast p + r_0 \ast K \ast (1-p) - K \ast (1-p) & C \cdot p < K \\
  r_0 \ast K \ast (1-p) + r_1 \ast (C-K) \ast p - (C-K) \ast p & C \cdot p > K 
\end{cases}
\]

(4.3)

It can be observed that for both \(C \cdot p < K\) and \(C \cdot p > K\) the coefficients for \(r_0\) and \(r_1\) are nonnegative. Therefore, the value of monitoring is an increasing function of the measures of information quality, \(r_0\) and \(r_1\).

This result is consistent with, and a specific case of, Blackwell's Theorem[1959]. Intuitively, Blackwell's theorem shows that if an information structure has an additional layer of 'randomness' as compared with another information structure, then its value can be no greater than the value of the other structure. Decreasing \(r_0\) or \(r_1\) is equivalent to increasing the randomness of the information structure. Therefore, the lower the values of \(r_0\) and \(r_1\), the lesser the value of the information structure and of monitoring. We can formally demonstrate this result.

A formal statement of Blackwell's Theorem is that information structure \(B\) is at least as valuable as information structure \(A\) if there exists a transformation matrix \(T_{AB}\) from \(B\) to \(A\) such that the column totals sum to one and the row totals are positive and finite. That is:
\[
T(a,b) = 1 \quad (4.4)
\]

and \(0 < \sum T(a,b) < \infty \quad (4.5)\)

The theorem can be used in the following manner to show that monitoring value is an increasing function of information quality.

Consider two information structures, A and B. The elements of these matrices, the conditional probabilities \(r_0\) and \(r_1\), we shall denote with the superscripts "a" and "b". We will assume that information structure A and B are such that:

\[
r_b^a > r_b^b \quad (4.6)
\]

\[
r_1^a > r_1^b \quad (4.7)
\]

Then, it is postulated that the matrix T shown below satisfies the criteria for Blackwell's Theorem.

\[
T = \begin{bmatrix}
    r_b^a r_1^b - (1-r_b^a)(1-r_1^b) & r_b^a(1-r_1^b) - r_b^a(1-r_1^b) \\
    r_b^a + r_1^b - 1 & r_b^a + r_1^b - 1 \\

    (1-r_b^a)r_1^b - (1-r_b^a)r_1^b & r_b^a r_1^b - (1-r_b^a)(1-r_1^b) \\
    r_b^a + r_1^b - 1 & r_b^a + r_1^b - 1
\end{bmatrix} \quad (4.8)
\]

The conditions that \(A = T*B\) and that the column totals sum to one (equation (4.4)) can be demonstrated with simple algebra. The last condition, inequality (4.5), that the row totals are positive and finite, requires some analysis. The row totals of T are:

\[
r_b^a(2*r_1^b-1) + (1-r_1^b)(2*r_b^a-1) \\
-------------------
           r_b^a + r_1^b - 1
\]
By our definition of the labels $y_0$ and $y_1$, the denominator of each of these terms is positive, so it is only necessary to demonstrate that each numerator is positive. From inequality (4.7) we have that:

\[
1 - 2r^q > 1 - 2r^q
\]  \hspace{1cm} (4.9)
\[
2(1-r^q) > 1 - 2r^q
\]  \hspace{1cm} (4.10)

From inequalities (4.6) and (4.7), we have that:

\[
\frac{r^q(2r^q - 1) + (1-r^q)(2r^q - 1)}{r^q + r^q - 1}
\]

\[
\frac{r^q(2r^q - 1) + (1-r^q)(2r^q - 1)}{r^q + r^q - 1}
\]

The left hand side of both (4.10) and (4.11) are positive, since $r_1 < 1$ and $r_0 + r_1 > 1$. Thus, multiplying (4.10) and (4.11) yields:

\[
2(1-r^q)(r^q + r^q - 1) > (1-2r^q)(r^q + r^q - 1)
\]  \hspace{1cm} (4.11)
\[
r^q(2r^q - 1) + (1-r^q)(2r^q - 1) > 0
\]  \hspace{1cm} (4.12)

Thus, the numerator of the first term is positive. A similar analysis can be used to demonstrate that the numerator of the second term is also positive. We may conclude, therefore, that the transformation $T$ satisfies the conditions of Blackwell's theorem. Therefore, information structure $B$ is at least as valuable as information structure $A$. The only difference between the two information structures, defined in inequalities (4.6) and (4.7), is that structure $B$ has higher quality information. Therefore, the results derived using our own analysis, equation (4.3), are consistent with Blackwell's Theorem. The value of monitoring is a direct function
of the quality of available information.

There have been several empirical tests of the relationship between information quality and the value of information. [Hilton, 1979; Ijiri and Itami, 1973; Wilson, 1975] Each of these studies was performed in a controlled laboratory setting. Subjects were asked to use information in a simulated decision context such as production scheduling and the experimenters generally varied the accuracy of information to study its effect upon the value of decisions made. Results in all three studies indicated a positive association between information accuracy and information value.

Thus, we have both theoretical and empirical support for the proposition that information quality is a positive determinant of the value of monitoring. The theoretical support is derived from our model of the value of monitoring and from application of Blackwell's Theorem to our monitoring context. The empirical support derives from accounting studies that have tested the relationship between information quality and information value in decision contexts other than monitoring.

We may conclude this section with a formal, testable hypothesis.

$H_1$: Information quality is a positively related determinant of monitoring value.
4.3 The Effect of Situation Uncertainty Upon Monitoring Value

Figure 4.1, which graphs the value of monitoring as a function of the prior probability that the situation is out of control, \( p \), illustrates that there is not a general monotonic relationship between \( p \) and monitoring value. This is also evident when equation (4.2) is refactored.

\[
VM = \begin{cases} 
  p\left[ (C-K)*r + K*(1-r_0) \right] - K*(1-r_0) & \text{C*p<K} \\
  -p\left[ (C-K)*(1-r_1) + K*r_0 \right] + K*r_0 & \text{C*p>K}
\end{cases} \tag{4.12}
\]

In the region where \( C*p < K \), \( p \) is positively related to monitoring value. In this region, without monitoring, the manager would choose not to intervene. The value of monitoring derives from correctly intervening when the need arises. The greater the value of \( p \), the more likely this is to occur. Thus, the positive relationship. The opposite results hold in the region where \( C*p > K \). Here, in the absence of monitoring, the manager will each period intervene. The value of monitoring in this case is obtained by correctly avoiding intervention when it is not required. The higher the value of \( p \), the less likely is intervention not to be required. Therefore, monitoring value in this region is a negative function of \( p \).

H2: When monitoring value is measured against the alternative of nonintervention, the probability of being out of control is a positively related determinant of monitoring value.

H3: When monitoring value is measured against the alternative of intervention, the probability of being out of control is a negatively related determinant of monitoring value.
From Figure 4.1 it is also evident that the value of monitoring is maximized at the point where \( C \cdot p \) is equal to \( K \). This represents the point at which the expected value of nonintervention is equal to the expected value of intervention. The value of monitoring model in equation (4.2) can be reformulated to illustrate this point.

\[
(4.13)
\]

\[
V_M = \begin{cases} 
\left(1 - \frac{K}{C}\right) \cdot K \cdot (1 - r_1) - \left(\frac{K}{C} - p\right) \left[\left(1 - \frac{K}{C}\right) \cdot r_1 + K \cdot (1 - r_0)\right] & \text{if } K/C - p > 0 \\
\left(1 - \frac{K}{C}\right) \cdot K \cdot (1 - r_1) - \left(-\frac{K}{C} + p\right) \left[\left(1 - \frac{K}{C}\right) \cdot (1 - r_1) + K \cdot r_0\right] & \text{if } -K/C + p > 0 
\end{cases}
\]

It can be observed that the maximum value of monitoring is \( (1 - \frac{K}{C}) \cdot K \cdot (r_0 + r_1 - 1) \). This value is achieved when \( p = K/C \). At this point, information signals have the maximum impact upon the expected value of intervention and nonintervention. We shall describe this point as the point of maximum uncertainty and define \(-|C \cdot p - K|\) as the uncertainty of the situation. Notice that the maximum value is obtained when \( p = K/C \). On either side of this point, the value of monitoring declines linearly as the uncertainty of the situation declines. Thus, situation uncertainty is a positive determinant of the value of monitoring.

There is empirical evidence that supports this proposition. Hilton[1979] used a simulated cost-volume-profit decision environment to study the effects of initial uncertainty upon information value. His results indicated a positive association. Weaker, but supportive results were obtained by Itami[1977] who concluded that information value was a nondecreasing function of initial uncertainty for the production planning situation under examination.
4.4 The Effect of Cost Structure Upon Monitoring Value

The structure of economic costs that define the manager's monitoring problem is arguably the most important determinant of monitoring value. The other elements of the monitoring model, p, r₀, and r₁, are all constrained to lie between zero and one. C and K are unbounded from above and only constrained to be positive. The range of values for C and K is quite large. For an unimportant situation, the difference in cost between in and out of control states may be near zero. For very important situations this value may be quite large. For example, many situations of competitive advantage or disadvantage are of great importance to senior managers. The difference in value between having competitive advantage, being in state s₀, and being at a competitive disadvantage, state s₁, may range into the millions of dollars.

When a manager monitors a situation, he is hoping to gain economic advantage by avoiding some cost or making some gain. When the alternative to monitoring is nonintervention, the cost he hopes to avoid is C-K, the gross benefit of not being out of control less the intervention cost. When constant intervention is the alternative to monitoring, the avoidable cost is that of intervention, K. Thus, the cost that the manager wishes to avoid depends upon what the strategy is without monitoring.

Rockart[1979] has defined critical situations as those areas of a manager's responsibilities in which the difference between good and poor performance has the greatest effect upon achieving the managers objectives. This definition is analogous to our definition of C as the
difference in value to the manager between the situation being in good or bad condition. Thus, in Rockart's terms, C is a measure of the criticality of the situation.

The model of the expected value of monitoring can be refactored in terms of C and K. This is done in equation (4.14).

\[
V_C = \begin{cases} 
C*r_1*p - K*[1-(1-r_0)*(1-p) + r_1*p] & \text{C*p<K} \\
-C*(1-r_1)*p + K*[r_0*(1-p) + (1-r_1)*p] & \text{C*p>K}
\end{cases}
\]

(4.14)

It is perhaps counterintuitive that the value of monitoring a situation is not always positively related to situation criticality. When nonintervention is the alternative to monitoring, when C*p<K, the coefficient of C is positive, but when intervention is the alternative, the coefficient is negative. In the second case, the basic strategy is to always avoid the critical cost C by intervening each period. Monitoring is used to determine when intervention is avoidable. A penalty of (C-K) is incurred each time the manager incorrectly avoids intervention. Therefore, the larger the value of C, the greater the penalty and the lower the value of monitoring.

We may summarize these discussions in the following two hypotheses.

**H4:** When monitoring value is measured against the alternative of nonintervention, situation criticality is a positive determinant of monitoring value.

**H5:** When monitoring value is measured against the alternative of intervention, situation criticality is a negative determinant of monitoring value.
4.5 A Summary and a Simplified Model of Monitoring Value

We have developed five hypotheses about determinants of the value of monitoring. They are consistent with the model of the expected value of monitoring developed in the last chapter. They are consistent with other theory, such as Blackwell's Theorem, and they are consistent with empirical evidence provided by several studies of the relationship between information value and the characteristics presently under consideration.

Taken together, these five hypotheses are not a complete representation of the value of monitoring model. One could not reconstruct the model from the hypotheses. It is possible, though, that for our purpose these hypotheses provide an adequate representation of the model. This we have formalized in the following hypothesis.

\[ H_6: \text{When monitoring value is measured against a single alternative of either intervention or nonintervention, information quality (IQ), the probability of being out of control (PR), and situation criticality (CR) significantly predict MV.} \]

If monitoring value is measured against the alternative of nonintervention, then we can use hypotheses \( H_1, H_2, H_4, \) and \( H_6 \) to construct the following simplified linear model of monitoring value:

\[ MV = IQ + PR + CR \tag{4.15} \]

If monitoring value is measured instead against the alternative of constant intervention, then hypotheses \( H_1, H_3, H_5, \) and \( H_6 \) can be used to construct an alternate linear model of monitoring value.
\[ MV = IQ - PR - CR \]  

(4.16)

These simplified models of monitoring value use a linear without any theoretical or empirical support. In the original model of monitoring value, equation (4.2) and in each of the refactored forms of the model, it is evident that the terms for information quality, probability of being out of control, and criticality combine in a multiplicative fashion. This leads to the following hypothesis:

H7: A multiplicative predictive model of MV provides significantly better fit than a linear form.

When the above hypothesis is combined with the previous hypotheses, alternative simplified models of monitoring value can be generated. In particular, when monitoring value is measured against the alternative that no intervention will be performed, then we have the following model:

\[ MV = IQ \times PR \times CR \]  

(4.17)

These three terms provide us with a parsimonious model of the value of monitoring any situation. The value of monitoring a situation is proportional to the product of information quality, the probability that the situation is out of control, and situation criticality. The situations most worth monitoring are those with a relatively higher joint product of these three factors.
4.6 A New Technique for IRA for Monitoring

Monitoring is a complex process. We have seen this in the development of these models. It can also be concluded from even casual observation of managers as they monitor situations. The complexity derives not only from the difficulty of using information to judge whether to act upon a situation, but also from the choice of which situations to monitor. We will use our model of how information is used in monitoring to provide a technique for determining which situations to monitor.

There is a strong need for such a technique. As Ackoff has observed, a major difficulty with many information systems is that they provide an overabundance of irrelevant information. [Ackoff, 1967] The same problem exists in monitoring. The range of situations that face a manager are so broad and so great, that it is difficult to isolate those situations where the limited time available for monitoring will provide the most value. Several techniques reviewed in the second chapter attempt to deal with this problem. The most successful of these is the Critical Success Factors technique. With this technique, a manager determines which situations are most critical to the attainment of his objectives. These are the situations designated for monitoring.

Our simplified model of the value of monitoring suggests that there are three factors that are important determinants of monitoring value, not just one. This model is the basis for a new technique for determining which situations to monitor. The new technique could be similar in implementation to the CSF technique. It could be
administered jointly by a manager and an expert in the technique to determine those situations which are most valuable to monitor. They would begin by concentrating upon the objectives of the manager. What is it that he is trying to accomplish in his position? How does he know when he is doing well? These types of questions can be used to develop a list of objectives and associated measures. Next, the manager and expert develop a pool of situations for consideration. This can be done with brainstorming focused upon situations that affect one or more of the objectives and that are not routinely corrected when no monitoring is performed. For each of these situations, measures are made of situation criticality, available information quality, and the average probability that the situation will need attention. If improvements in information systems are also contemplated, then the manager and expert should estimate the information quality expected rather than existing. The average probability can be estimated by focusing upon some fixed time horizon, such as six months, and asking what the probability is that the situation will need intervention at some time during that period. With each of these measures in hand, the value of monitoring each situation can be estimated by multiplying the scores on each of the three factors. The situations with the highest estimate of monitoring value are those that are worthy of monitoring effort.

This new technique can also be used for other purposes, such as selecting situations for information systems improvement, but this is getting ahead of ourselves. First we must test the underlying simplified model of monitoring value. If it our three factors are a valid predictor of monitoring value, then we can explore other uses for
this model. In the next chapter, several empirical tests of our model are performed.
5 A TEST OF THE VALUE OF MONITORING MODEL

5.1 Introduction

The simplifications made to the economic models of monitoring value were cast in chapter four as a series of seven hypotheses. Taken together, they form a simplified model of monitoring value that can be used in a new technique for information requirements analysis for monitoring. The technique helps managers to determine which situations are most worth monitoring. Since it is a simple corollary of the value of monitoring model, our validation efforts should be centered upon showing that that model is correct. It is incumbent upon us to provide some test of our claim that the simplified model adequately predicts monitoring value.

The value of monitoring is equal to the economic improvement expected as a result of monitoring efforts. It is measured against a base case that no monitoring is performed. We have included two base cases in our model, to reflect rational economic behavior in the absence of monitoring. In one case, the alternative to monitoring is to intervene each period, just in case the situation is out of control. In the other case, the alternative is to do nothing. Depending upon which case is chosen, the form of the simplified model of monitoring value is somewhat different.

For both cases, monitoring value is determined by information quality, the probability that the situation is out of control, and
situation criticality. When measured against the alternative case of nonintervention, monitoring value is positively determined by those three factors. Further, from the form of the models of information value explored in chapter three, it can be postulated that these factors combine in a multiplicative fashion. Thus, when measured against the alternative of nonintervention, we have that:

\[ MV = IQ \times PR \times CR \]  

(5.1)

where \( MV, IQ, PR, \) and \( CR \) represent monitoring value, information quality, the probable need for intervention, and situation criticality, respectively.

There are several reasons for us to doubt the validity of the above model. First, in deriving the model we have used several assumptions, approximations, and simplifications. Each may have been justifiable. Yet, in the process of developing our model of the value of monitoring, the compound effects of minor deviations from reality may be to invalidate our results. A series of minor deviations from reality, one piled atop another, can accumulate into significant systematic error.

A second reason for doubt as to the validity of our new information requirements analysis technique for monitoring is that it rests upon our ability to operationalize the model. Criticality, information quality, and the probable need for intervention may jointly be perfect predictors of the value of monitoring, but if they cannot be detected and measured, then we do not have a technique. Our objective has been to produce theory that is both logical and practical. It is incumbent upon us to show that our model and our technique can be
Finally, it is an empirical matter as to whether all three terms in our value model are important. It may be that there is so little variation from situation to situation in one of the terms that it could be dropped without damage to the model. It may be that one term overwhelms the significance of the other two. Certainly Rockart's critical success factor methodology is based upon that premise. Only through empirical testing can we determine whether further simplifications can be made.

There are three tests of the value model that need to be provided. The first test is of the form of the model. Is there evidence that a multiplicative form is superior to a simpler, linear form? If not, then we may prefer to simplify matters with a linear model. The second test is of the ability of the three terms CR, IQ, and PR to determine the value of monitoring. It may be that in our model development we have omitted important variables that should be considered. Ideally, our three terms would predict with one hundred percent accuracy the value that a manager obtains from monitoring a situation. In practice there are at least three impediments to achieving this. First, our approximations and simplifications in model development have assured us that there is not a perfect fit between the model and reality, but we have some confidence that this is not a major problem. Second, each of the concepts in our model cannot be measured with complete accuracy. Therefore, measurement error alone will result in less than perfect predictions. Finally, our model is a model of the expected value of monitoring a situation. Through random chance, what is expected may not be obtained. The final test of the model is of the
relative significance of each of the independent terms. It may occur that two of the factors correlate very strongly or that a factor provides insignificant incremental predictive power to our model. Then it may be possible to drop one or more of them if results indicate that the others provide the dominant predictive ability.

5.2 Method

5.2.1 Research Design

The present study can be considered a minimal quasi-experiment of a type described by Cook and Campbell. [1979] The investigation uses a posttest-only design with a single group, multiple covariates, and measurement error explicitly modeled. The criticality, information quality, probable need for intervention, and value obtained from monitoring were observed for a large number of situations. The test of the model is of whether it is consistent with the observed data.

5.2.2 Research Instrument

Measures of criticality, information quality, probable need for intervention, and value of monitoring were obtained using a survey instrument. The instrument was developed specifically for this study. It underwent three revisions as a result of pretesting. The final version is attached as Exhibit A.

The instrument that was finally used asked the respondent to list in any order ten situations that he routinely monitored. Each characteristic of a situation, such as criticality, was then measured
relative to the other situations on the list. In this manner, absolute
measures were not obtained, but at the benefit of only requiring
respondents to make simple comparisons between situations of their own
choosing.

Questions were of two types. One type asked the respondent to
choose the situation that most exhibited some characteristic (such as
criticality) and the situation that least exhibited the same
characteristic. Using these situations as endpoints on a twenty-one
point scale of that characteristic, the respondent was next asked to
indicate the relative position of the other situations. The second
type of question provided a twenty-one point scale for each situation.
Each scale was anchored on both ends by extreme values of some
characteristic (such as very volatile and very stable) and the
respondent was asked to indicate on each scale the position that best
indicated the characteristic of the corresponding situation.

For the variables MV, IQ, and PR, three separate questions were
asked. Difficulties with one measure of criticality left us with only
two measures for it. The measure in question asked respondents about
the relative value of corrective actions in response to a situation
being out of control. Although an intended measure of criticality, use
of the word 'value' made the question ambiguous and confusing. In
addition, measures of other variables not relevant to this
investigation, were also obtained.

Criticality: The relative criticality of each situation was
measured with the following items. One item (CR1) asked:

Using the following scale, please indicate for each
situation your degree of concern at being told by a trusted
peer, "We've just discovered a major difficulty with
situation X."
The scale was anchored at the ends by the labels "very concerned" and "unconcerned". The second item (CR2) asked the respondent "For which situation would you most hate to see something go wrong? For which situation would you least hate to see something go wrong?" It then instructs the respondent to use these situations as endpoints on a twenty-one point scale and to indicate "the relative degree of displeasure" for each situation by marking the situation's number on the scale at the appropriate position.

These two items measured criticality by requiring the respondent to reflect on the consequences if each situation was out of control. It was necessary to separate in the respondent's mind the consequences of a situation being out of control from the probability that the situation was out of control. Criticality is concerned with the former, not the latter. Our success at having respondents distinguish between criticality and volatility contributes to the content validity of the instrument. This will be tested in this chapter.

Information Quality: The relative quality of available information for each situation was measured with the following three items. One item (IQ1) asked, "Using the following scale, please indicate the amount of information you usually have available to monitor each situation." For each situation, the scale was anchored from "all" to "none" of the information necessary to form a complete picture. The second item (IQ2) provided a preamble designed to have the respondent think broadly about his information sources. It then asked for the situation with the most complete information available and the situation with the least complete information available. Again these were used as endpoints on a scale on which the other situations
were marked.

The third item (IQ3) approached the information quality variable indirectly. Higher quality information provides greater insight into the condition of a situation. Therefore, information quality can be measured by the residual uncertainty that remains after the information has been reviewed. The item asked:

Assume, for the moment, that you have just reviewed all of your formal and informal sources of information for each situation. Please indicate on the following scales the degree to which you would still be uncertain about the exact status of each situation.

The scales were anchored by "completely uncertain about its status" and "completely certain about its status".

Probable Need for Intervention: The likelihood that the situation is in poor condition was measured with the following three items. One item (PRI) asked "Using the following scale, please indicate for each situation the probability that the situation will need some significant managerial action on your part during the next six months". The scales were anchored with "certainty" and "no possibility". A second item (PR2) asked, "Using the following scale, please indicate for each situation the probability that the condition of the situation presently warrants some type of major managerial action on your part". This item employed eleven point scales for each situation, with each point labeled from "no possibility" to "certain". The last volatility item (PR3) asked for an indication of "the likelihood that the situation will be in need of managerial action at some time during the next three months". The twenty-one point scale was anchored by "very likely to be in need of managerial action" and "very unlikely to be in need of managerial action".
Monitoring Value: Three items were used to measure the respondents' perceptions of the value they obtained from monitoring different situations. The first item (MV1) asked to "indicate for each situation the value you expect to receive, during the next year, from monitoring that situation." The anchors on the scale were "of very little value" and "extremely valuable". Another item (MV2) asked the respondent to identify the situation for which monitoring has yielded the greatest value during the past six months and the situation for which the value was least. These situations anchored a scale on which the respondent was asked to place the other situations. The last monitoring value item (MV3) used the same scale anchors as MV1, but asked the respondent to indicate the value received from monitoring the situation during the last year.

In each of these three questions, the respondent was asked for the value of monitoring, without an explicit baseline specified. The alternative against which value was to be measured was not specified. In this case, the respondent was assumed to estimate the value of monitoring against the baseline action of nonintervention.

5.2.3 Subjects and Procedure

The questionnaire was administered to middle level managers drawn from four companies in the Boston area. In each case, the manager's prior cooperation was obtained for a study on "managerial monitoring behavior". The manager was then visited at his company and provided with a verbal explanation of how to fill out the questionnaire. Assistance was provided in listing ten situations that the manager monitored by providing examples of potential situations. Each
respondent was instructed on the two types of questions, instructed not to refer to previous questions as they filled out the questionnaire, and asked to return the completed questionnaire by mail within seven days.

A total of fifty-two questionnaires were distributed. Thirty-nine were returned and of these all but one was complete. Therefore the analyses were performed on the data obtained from thirty-eight respondents. The unit of analysis for testing the value of monitoring model is the situation. Thus the thirty-eight respondents provided a pool of data on three hundred and eighty situations. The potential error introduced by pooling a number of situations from each respondent is the subject of the next section.

5.3 Analysis of Pooling of Data

Figure 5.1 presents the variance covariance matrix, correlation matrix, and means for the data obtained from the 38 subjects responding to eleven questions about each of their ten situations. These values are based on a power transformation \( x = d^{1.5} \) applied to the original data \( d \) for purposes of eliminating the skew of the distribution of responses. The planned statistical analyses are based upon the assumption that the data are multivariate normal and in some cases they are sensitive to departures from this assumption. The transformation resulted in 'more normal' data. The statistics were computed across all 380 situations. When these statistics are interpreted and used for further analysis, it is a common assumption that all observations are randomly selected. This condition would be fulfilled if the data had
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Means: 60.370 45.989 52.187 59.011 51.519 51.887 44.050 53.047 56.706 40.328 53.421

Standard errors shown in parentheses

Variance Covariance Matrix, Correlation Matrix, and Means
For Data From Ten Pooled Situations

Figure 5.1
been obtained from 380 randomly selected subjects, each asked for responses about one situation. But in our case, data obtained from each respondent about ten different situations has been pooled. In this section we will analyze that data to determine whether pooling will affect further analysis.

There are two types of problems that can be introduced by pooling the data collected on ten different situations. The first problem occurs if the relationship between measures differed from situation to situation. When they were pooled, the aggregate correlation structure would reflect only some average of the relationships between measures. A second problem can occur if the pooling of situations serves to inflate or deflate the overall relationship between measures.

Neither of these problems occur if the measure variance covariance matrices for each situation and for the pooled data are equal. This condition can be tested using the LISREL V statistical package. [Joreskog and Sorbom, 1981] To do this, we represent the variance covariance matrix among measures as a structural equation model and use the data from the ten situations to estimate ten models, under the constraint that the matrices must be equal. If the ten situations are equivalent, then the data will provide a statistically significant fit to the model. A structural equation model of the measurement variance covariance matrix is diagrammed in Figure 5.2. This and all other structural equation figures will follow the conventions of causal analysis. "Latent variables are drawn as circles and indicated with upper case letters and numerals. Attitudinal measures are presented as squares and indicated with lower case letters and numerals; causal and measurement relations are shown as arrows;
Structural Equation Model for Measurement Variance Covariance Matrix

Figure 5.2
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Estimated Variances and Correlation Matrix for Structural Model
Of Equal Covariance Structure for All Ten Situations

Figure 5.3

standard errors shown in parentheses
error or unique factors are also represented as arrows but without
origin; and parameters to be estimated are depicted as Greek

Figure 5.3 presents the results for the model hypothesizing that
the measurement variance covariance structures for the ten situations
are equal. Figure 5.4 presents the indicators of goodness of fit of
the estimated model to the data from each situation. The goodness of
fit index (GFI) is a measure of the relative amount of variance and
covariance jointly accounted for by the estimated model. The GFI
results indicate that the shared variation among situations ranges from
52.7% to 70.1%.

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d.f. = 66

Figure 5.4

The overall fit of the model of equivalent variance covariance
structures to the data is summarized by the chi-square statistic.
Joreskog and Sorbom write, "Instead of regarding \( \chi^2 \) as a test
statistic one should regard it as a goodness (or badness) of fit
measure in the sense that large \( \chi^2 \) values correspond to bad fit and
small \( \chi^2 \) values to good fit. The degrees of freedom serve as a
standard by which to judge whether \( \chi^2 \) is large or small." [p. 1.39] By
convention, a model is considered to provide an acceptable fit if the probability of obtaining a $\chi^2$ value larger than the value actually obtained is greater than 0.05. For the model at hand, the chi-square statistic is $\chi^2(594) = 690.92$, $p = .004$. This provides an unacceptable fit to the data and is an indication that there is some nonequivalence of data across situations.

Which situations are nonequivalent can be determined in two ways. One approach is to construct two structural equation models constrained to be equal, with one representing the measurement variance covariance structure for a particular situation and the other representing the structure for the rest of the situations pooled. If for a particular situation, the model provides a good fit to the data, then it may be concluded that the situation is approximately equivalent to the pooled sample under examination. If there is a lack of fit, then this is an indication that the situation under examination is significantly different from the others. A second test can be made by comparing the fit of data for every pairing of situations to a model of two variance covariance structures constrained to be equal. The first test has the advantage of testing for both types of problems that can be introduced by nonequivalent pooled situations. A situation will show poor fit either if it is different from other situations or if it is different from the aggregate structure. The second test has the advantage of providing detailed insight into where any lack of equivalence exists.

Both tests were performed on the data and the results are shown in Figures 5.5 and 5.6. The first test indicates that two situations, number one and number seven, have measurement variance covariance matrices that are significantly different from the variance covariance
structure of the pool of other situations. The probabilities associated with the chi-square statistic were 0.005 and 0.020 respectively, below the 0.05 level.

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d.f. = 66

Fit Between Covariance Matrices of Situation and Rest of Pool

Figure 5.5

Of the 45 two way comparisons of variance covariance structures reported in Figure 5.6, fifteen are not significant. Six of these poor fits can be attributed to situation one and five to situation seven. When these situations are removed from consideration, there are only four nonsignificant fits among the 28 remaining pairs. No situation is a part of more than two of them. The chi-square probability for these four cases are 0.041, 0.031, 0.014, and 0.012, indicating that the lack of equivalence is not severe.
The two tests provide consistent results. They indicate that situations one and seven are not equal to the rest of the situations. Therefore, they should not be included in any pooling of data.

Before we conclude that the rest of the situations may be pooled, we must rerun the tests of equivalence for the pool of eight remaining situations. For the model in which we estimate eight variance covariance structures, all constrained to be equal, the overall fit of
### Table: Estimated Variances and Correlation Matrix for Structural Model

Of Equal Covariance Structure for Eight Situations

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*standard errors shown in parentheses*
the model is acceptable. The chi-square statistic is 
\( \chi^2(462) = 499.19, p = 0.112 \). Figure 5.7 presents the estimates of this model. Figure 5.8 presents the indicators of goodness of fit of the estimated model to the data from each situation. The GFI results indicate that the shared variation among situations ranges from 61.2% to 69.6%.

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d.f. = 66

Figure 5.8

The second test is the comparison of each variance covariance matrix to the matrix that results from pooling the other seven situations. The results are shown in Figures 5.9.
The results of this second test indicate that there is strong equivalence among the remaining eight situations. In all cases, there is acceptable fit of the model that hypothesizes that the variance covariance structure of each situation is equal to the variance covariance structure of the pool of remaining situations. Therefore, further analysis will be performed on a group of 304 situations, formed by pooling all but the first and seventh situation from each respondent. The variance covariance matrix, correlation matrix, and means for this data are provided in Figure 5.10.

Comparison of Figure 5.10 with the variance covariance matrix across all ten situations, shown in Figure 5.1, indicates very little difference. This is to be expected, since they share the majority of data. Equivalence of these two variance covariance structures was tested with a structural equation model. The fit of the data to the model was very good. The chi-square statistic was $\chi^2(66) = 12.26$, $p = 1.000$. Therefore, removal of the two nonequivalent situations from
### Variance Covariance Matrix, Correlation Matrix, and Means
For Data From Eight Pooled Situations

#### Table

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<th>CR2</th>
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<td>(38.916)</td>
<td>(38.916)</td>
<td>(38.916)</td>
<td>(38.916)</td>
<td>(38.916)</td>
<td>(38.916)</td>
</tr>
</tbody>
</table>

Standard errors shown in parentheses.

Figure 5.10
the pool has not significantly changed the relationships between measures.

Before concluding this analysis, it is worth reflecting on why two situations had nonequivalent measure variance covariance structures. In one case, the interpretation is rather straightforward, but in the other it is not. The easier case is the first situation. This is the situation that each respondent first placed on their list of ten situations. Its data may have been different for two reasons. First, the situation may have had unusual characteristics. It was the most salient situation, perhaps the most important situation, to have been the first one entered by each respondent. Second, because it was at the top of the list each time a question was answered, it was more directly in view. When a question asked which situation was extreme in some dimension, a scan of the list most likely began with the first situation. Thus, because of salience and position on the list, it is understandable that the data obtained for this situation was different from the rest.

The seventh situation is more puzzling and more difficult to interpret. It can be observed in Figure 5.9 that there is a general decrease in equivalence for the eighth, nineth, and tenth situations. Thus, one might speculate that there is indeed something magic about the number seven.

A note of caution should be introduced before finally leaving this section. The chi-square statistic that we have been using to examine the fit of our hypothesized models only approaches the chi square distribution asymptotically. In several of our tests, the sample size was only 36, well below the recommended size of about one
hundred needed to assure good compliance with the distribution. With a smaller sample, the chi square statistic would tend to be overestimated by the data. Therefore, these statistics should not be used as part of likelihood ratio tests. Instead, as Joreskog and Sorbom have recommended, they have been used as goodness of fit measures.

5.4 Analysis of Instrument and Data Quality

The eleven questions in the instrument were used to measure four distinct characteristics of each situation: criticality, information quality, the likelihood of needing intervention, and value obtained from monitoring. The latter characteristic is our dependent variable. The other three are hypothesized to predict it. Before we can begin to analyze the hypotheses formed in the last chapter, it is necessary to examine the quality of our instrument.

5.4.1 Convergent Validity

Convergent validity refers to whether the measures of a construct correlate higher with each other than they do with measures of other constructs. It is an indication that the measures actually measure the characteristics under consideration. The assumption is that if a set of items is really measuring some underlying trait or attitude, then the underlying trait causes the covariation among the items. The higher the correlations, the better the items are measuring the same underlying construct. [Bohrnstedt 1969, p. 92] Three statistical tests of convergent validity can be used. First, the correlation table of measure scores can be visually inspected for violations. These occur
if a measure correlates higher with a measure of another construct than
with another measure of its own construct. Second, the measure scores
of the independent characteristics (IQ, PR, and CR) can be factor
analyzed. If there are three underlying constructs, then the measures
should load only on their own construct and the loadings should be
fairly uniform. The third, and more powerful test of convergent
validity is to examine the fit of the data to a confirmatory factor
analysis model of the following form.

\[
y = \Lambda \cdot x + \theta \\
= \Lambda \cdot \phi \cdot \Lambda' + \epsilon
\]  

(5.2)  

(5.3)

where \( y \) is a vector of our eight independent measures, \( x \) is a
vector of the three independent constructs, \( \phi \) is the correlation
matrix among constructs, \( \Lambda \) is a matrix of factor loadings relating \( y \) to
\( x \), \( \theta \) is a vector of error terms, \( \Sigma \) is the measure covariance matrix,
and \( \epsilon \) is a diagonal matrix of error variances for the measures. For
the hypothesis that the eight measures load only onto their associated
constructs, we fix the factor loadings of measures onto other
constructs to be zero. A diagram of the model is shown in Figure 5.11.

The correlation of measure scores is shown in Figure 5.10. Of
the 55 correlations, none is in violation of the rule that measures of
the same characteristics should correlate more highly with each other
than with measures of other characteristics. This supports the
hypothesis that the eight independent measures are caused by the three
underlying constructs.

A factor analysis was performed on the scores obtained from the
eight measures of the three independent constructs. The results of the
analysis are shown in Figure 5.12. The eigenvalues indicate that only the first two factors significantly explain the variation in the measure scores. The eigenvalue of the third factor is less than 1.00, even though it does explain almost twelve percent of overall variation. It is evident from the factor loadings that the measures load onto three separate factors that conform to our concept of situation characteristics. The first factor is closely associated with the probable need for intervention. Only PR measures load heavily on this factor. The second factor only has information quality measures loading heavily on it and the third has only criticality measures. Thus, the factor analysis provides evidence for the convergent validity of the measurement instrument. The measures cluster into three factors that closely correspond to the three independent characteristics. The low eigenvalue of the third factor forewarns of potential problems in the test of our monitoring value model.

<table>
<thead>
<tr>
<th>FACTOR</th>
<th>FACTOR</th>
<th>FACTOR</th>
</tr>
</thead>
<tbody>
<tr>
<td>ONE</td>
<td>TWO</td>
<td>THREE</td>
</tr>
<tr>
<td>PR1</td>
<td>-0.872</td>
<td>0.047</td>
</tr>
<tr>
<td>PR2</td>
<td>-0.656</td>
<td>-0.133</td>
</tr>
<tr>
<td>PR3</td>
<td>-0.778</td>
<td>0.087</td>
</tr>
<tr>
<td>IQ1</td>
<td>0.120</td>
<td>0.788</td>
</tr>
<tr>
<td>IQ2</td>
<td>-0.010</td>
<td>0.846</td>
</tr>
<tr>
<td>IQ3</td>
<td>-0.084</td>
<td>0.763</td>
</tr>
<tr>
<td>CR1</td>
<td>-0.162</td>
<td>0.655</td>
</tr>
<tr>
<td>CR2</td>
<td>-0.096</td>
<td>0.021</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variation Explained</th>
<th>28.3%</th>
<th>24.4%</th>
<th>11.9%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigenvalue</td>
<td>2.16</td>
<td>1.86</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Varimax Factor Loadings of Independent Measures

Figure 5.12
The third test of convergent validity is provided by the confirmatory factor analysis model in Figure 5.11. Estimates for that model are shown in Figure 5.13. Each of the parameters is significant at the 5% level, except for the correlation between information quality and probable need for intervention. The confirmatory factor model did not provide a good fit to the data. The chi-square statistic for this model is $\chi^2(17) = 46.15$, $p = 0.000$. Although the two previous tests provided support for the hypothesis of convergent validity, this more powerful test leads us to rejection of that hypothesis.
Examination of the diagnostic statistics provided by the LISREL V package indicates that a satisfactory fit was not achieved because one measure of information quality (IQ1) loaded on the PR construct and one measure of the probable need for intervention (PR2) loaded on the IQ construct. The IQ1 question asks the respondent about the amount of
information presently available. It is likely that respondents determined the amount of information relative to their need for it and that that need increased as the probability of needing intervention increased. That is, the more likely the need for intervention, the less information a respondent would perceive he has. Thus, we might expect IQ1 to load negatively on PR. The PR2 measure asks the respondent about the probability that the situation presently warrants some form of intervention. A response to this question could reflect not only the underlying probability that the situation needs intervention, but also the respondent's uncertainty about the condition of the situation. Thus, we would expect that PR2 loads negatively on IQ.

A diagram of the factor analysis model implied by these changes is shown in Figure 5.14. Estimates for that model are shown in Figure 5.15. Again, except for the correlation between information quality and probable need for intervention, each of the parameters is significant at the 5% level. These insignificant intercorrelations are not a concern here, since the intercorrelations among independent constructs are exogenous factors whose magnitudes are unimportant to the model. The factor model provides a good fit to the data. The chi-square statistic for this model is $\chi^2(17) = 21.50$, p. = 0.205.
Revised Structural Equation Model for Test of Convergent Validity

Figure 5.14
This measurement model must be accepted with some caution. The original hypothesized convergent validity model was rejected. This present model was constructed from an exploration of the data. Thus, the fit is only confirmation that the exploration has been correctly
performed. In support of this model we have two types of evidence. First, the modifications made to the original confirmatory factor analysis model are small. Only two loadings needed to be added and the estimates for these, while statistically significant, were small in value. The goodness of fit index for the original model was GFI = 0.925. The index for the revised model was GFI = 0.977. In both cases more than ninety percent of the variation in the data was accounted for by the model. The modified model provided only a marginal increase in the GFI. The second support for this revised model is provided by the presence of logical explanations for the two additional loadings. These are only post hoc rationalizations for why the loadings should be added, but they are reasonable and appealing. In conclusion, the original hypothesis of convergent validity must be rejected, but there is reasonable support for the revised convergent validity model that cannot be rejected by the data.

5.4.2 Reliability

Reliability in the context of measurement theory refers to the consistency of measures, both over time and across a set of measures which purport to measure the same characteristic. Reliability of a measure over time is generally tested by measuring a number of entities at two points in time, and correlating the results across entities. The higher the correlation, the greater the intertemporal reliability. In this empirical study, no attempt was made to test the reliability of the instrument over time.

The second type of reliability, across a related set of measures, is usually tested by means of a Cronbach alpha coefficient.
This statistic is an estimate of the equivalence of each of the measures as an indicator of the underlying variable. It is computed as follows:

\[
\alpha = \frac{n}{n-1} \left( 1 - \frac{\text{sum of measure variances}}{\text{variance of sum of measures}} \right)
\]

where \(n\) is the number of measures of the underlying variable. A Cronbach alpha coefficient greater than 0.7 is generally considered adequate for field research. In Figure 5.16, the alpha coefficients and other relevant information for our measures, are listed.

<table>
<thead>
<tr>
<th>CHARACTERISTIC</th>
<th>AVERAGE INTERITEM CORRELATION</th>
<th>CRONBACH ALPHA COEFFICIENT</th>
<th>ALPHA IF ITEM DELETED</th>
<th>MEASURE</th>
</tr>
</thead>
<tbody>
<tr>
<td>MV</td>
<td>0.587</td>
<td>0.808</td>
<td>0.805</td>
<td>MV1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.710</td>
<td>MV2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.682</td>
<td>MV3</td>
</tr>
<tr>
<td>IQ</td>
<td>0.635</td>
<td>0.838</td>
<td>0.785</td>
<td>IQ1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.736</td>
<td>IQ2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.798</td>
<td>IQ3</td>
</tr>
<tr>
<td>PR</td>
<td>0.598</td>
<td>0.818</td>
<td>0.667</td>
<td>PR1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.628</td>
<td>PR2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.735</td>
<td>PR3</td>
</tr>
<tr>
<td>CR</td>
<td>0.500</td>
<td>0.719</td>
<td>-</td>
<td>CR1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-</td>
<td>CR2</td>
</tr>
</tbody>
</table>

Reliability Coefficients

Figure 5.16

As is indicated in Figure 5.16, the Cronbach alpha coefficients for each group of measures is satisfactory. The lowest coefficient has a value of 0.719. Consistent with this result are the high average values for the correlations between measures of the same
characteristic. Figure 5.16 also shows the alpha coefficient values if any particular measure were removed from its group. The results indicate that only in one case would the reliability of the composite measure of a characteristic be improved by dropping a measure. The overall reliability of a composite volatility measure would be improved slightly, from 0.818 to 0.828, if the PR2 measure was dropped. The slight difference in reliability is not sufficient to cause us to drop PR2 as a volatility measure. This result does, though, alert us to a measurement problem that should be corrected for our test of the monitoring value model.

5.4.3 Concurrent and Discriminant Validity

Concurrent validity is attained when measures of the independent constructs covary with measures of the dependent construct to a significant extent. Discriminant validity exists when uniqueness is demonstrated by all constructs. A confirmatory path analysis model can be used to test for both concurrent and discriminant validity. Figure 5.17 illustrates the path model that will be used for this purpose. To sustain the hypothesis of concurrent validity, the correlations between constructs in the path model must be high and statistically significant. To sustain the hypothesis of discriminant validity, these correlations must be significantly different from one.

Figure 5.18 presents the intercorrelation matrices among the latent constructs MV, IQ, PR, and CR. The goodness of fit index is GFI = 0.927, indicating that more than 90% of the shared variation among measures was captured by the model. The chi-square value for the model is $\chi^2(38) = 96.51, p = 0.000$, indicating that this model did not
Structural Equation Model for Tests of Concurrent and Discriminant Validity

Figure 5.17
achieve a significant fit to the data, despite the high GFI result. The resultant intercorrelation matrix between constructs is shown in Figure 5.19. With the addition of three correlated error terms between (MV1, CR1), (MV3, IQ1), and (IQ3, PR3) the model achieved significant fit. The chi-square statistic was $\chi^2(35) = 44.32$, $p = 0.134$; the goodness of fit indicator increased marginally to GFI = 0.963. The revised intercorrelation matrix is shown in Figure 5.20.

<table>
<thead>
<tr>
<th></th>
<th>MV</th>
<th>IQ</th>
<th>PR</th>
<th>CR</th>
</tr>
</thead>
<tbody>
<tr>
<td>MV</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IQ</td>
<td>0.270</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.065)</td>
<td>(0.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PR</td>
<td>0.613</td>
<td>0.129</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.069)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>CR</td>
<td>0.746</td>
<td>0.137</td>
<td>0.340</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.072)</td>
<td>(0.067)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

$n = 304$

Estimated Intercorrelations Between Constructs
For The Path Model of Figure 5.18

Figure 5.19
The addition of correlated error terms to a structural equation model must be made with caution. In our case, we can test whether the addition of the terms significantly affected the estimates of intercorrelations between constructs. If it did not, then it is appropriate to run the tests of convergent and discriminant validity on either tableau of intercorrelations. To test for equality of intercorrelation estimates, two estimates must be made. First, the two models must be estimated under the constraint that the construct intercorrelations are equal in both models. The second estimates are made with the parameters free. The difference in chi-square statistics between these two estimates is a test statistic of the significance of the equality constraint. It has a chi-square distribution with degrees of freedom equal to the difference in degrees of freedom between the two models. If the constraint is found to be insignificant, then it
may be concluded that the two intercorrelation matrices in Figures 5.19 and 5.20 are equal. The estimates were computed with the following results. For the estimates made under the constraint of equal construct intercorrelations, \( \chi^2(79) = 141.49 \). When this constraint was dropped, the obtained chi-square was simply the sum of those previously obtained for the two models, \( \chi^2(73) = 140.83 \). The difference between these two, \( \chi^2(6) = 0.66, p = 0.004 \), is insignificant and indicates that the additional constraint is insignificant. Therefore, the hypothesis of equal construct intercorrelation structures across the two models is sustained.

For concurrent validity, the important correlations are those between monitoring value (MV) and the three independent variables, CR, IQ, and PR. Each of these correlations is positive and significantly different from zero. Therefore, concurrent validity is achieved. To test for discriminant validity, one must determine whether all the correlations in Figure 5.20 are significantly less than unity. Inspection of the correlations and their confidence intervals indicates that discriminant validity is also sustained.

### 5.5 Test of the Multiplicative Form of the Model

In the beginning of this chapter, three tests of the monitoring value model in equation 5.1 were planned. The first test is of the multiplicative form of the model, the second of the predictive power of the independent terms and the third of the relative significance of each independent term. In the last section we established the convergent, concurrent, and discriminant validity and the reliability
of the instrument used to gather data for the tests. In this section, we examine hypothesis H7 developed in the last chapter. That hypothesis is:

\[ H7: \text{A multiplicative predictive model of } MV \text{ provides significantly better fit than a linear form.} \]

### 5.5.1 Hierarchical Regression

We have derived a model for the value of monitoring using certain assumptions about the nature of managerial monitoring behavior. Our theory is that three independent variables determine the value of monitoring and that they combine multiplicatively. A simple alternative to this model would be a linear form, using the same independent variables.

\[
MV = b_0 + b_1 \times CR + b_2 \times IQ + b_3 \times PR \tag{5.2}
\]

Hierarchical regression provides a test of whether the multiplicative form is more powerful than a linear form and this test can be performed on interval scale data, such as was collected by our instrument. [Arnold and Evans, 1979; Cohen, 1978] The transformation performed on the data to reduce skew does not preserve the interval form of the data. Therefore, in this section tests will be performed using the raw data. Hierarchical regression will not test whether the linear form of the model provides a better fit of the data, but only whether it is as good as the multiplicative model.

This test is important to us for two reasons. First, if the multiplicative form is found to be more powerful, then this provides some confirmation of our derived monitoring value model. Rejection of
a linear form in favor of a multiplicative form can occur only if each independent variable is a significant predictor of monitoring value and if the functional form is truly nonlinear. Second, the greater the extent to which our data displays nonlinear characteristics, the lesser the appropriateness of linear analysis techniques. This is important because there are no powerful techniques for analysing nonlinear models using interval scale data.

The testing approach of hierarchical regression is to compare the fit of the simple linear model with a model that includes all the two way interactions and with a model that includes all two way interactions and the three way interaction. If the addition of interaction terms provides a significant improvement in the fit of the model, then the multiplicative form is deemed to be more powerful than the simple linear form. If the improvement in fit is not significant, then one may conclude that the linear model is as powerful as a multiplicative form.

Three regressions models must be estimated. These are shown below.

A: \[ MV = b_0 + b_1 \cdot CR + b_2 \cdot IQ + b_3 \cdot PR \] (5.3)

B: \[ MV = b_0 + b_1 \cdot CR + b_2 \cdot IQ + b_3 \cdot PR + b_4 \cdot CR \cdot IQ + b_5 \cdot CR \cdot PR + b_6 \cdot IQ \cdot PR \] (5.4)

C: \[ MV = b_0 + b_1 \cdot CR + b_2 \cdot IQ + b_3 \cdot PR + b_4 \cdot CR \cdot IQ + b_5 \cdot CR \cdot PR + b_6 \cdot IQ \cdot PR + b_7 \cdot CR \cdot IQ \cdot PR \] (5.5)

To test whether equation B provides a significantly better fit to the data than equation A, and in turn whether C exceeds B, one forms the F ratio:
\[
F = \frac{R_2^2 - R_1^2}{\frac{n - k_1 - k_2 - 1}{k_2}} \frac{n - k_1 - k_2 - 1}{(1 - R_2^2)} \quad (5.6)
\]

where \( R_1^2 \) is the \( R^2 \) for the first linear model, \( R_2^2 \) is the \( R^2 \) for the second linear model, \( n \) is the sample size, \( k_1 \) is the number of independent variables in the first model, and \( k_2 \) is the number of terms added to form the second model. This F ratio has \((k_2, n-k_1-k_2-1)\) degrees of freedom. [Arnold and Evans 1979, p. 44]

5.5.2 Results

The first hierarchical regression test was performed on the raw data from all 304 situations. The hierarchical regression test requires scores for MV, IQ, PR, and CR. Scores were computed as the unweighted average of each construct's underlying measures. The results of the regression analysis are shown in Figure 5.21. They indicate that addition of two way interaction and three way interaction terms to the regression provides only a marginally better fit (increasing the \( R^2 \) by 0.028 and 0.016, respectively). These increases in fit are not statistically significant. The corresponding F ratios fail to exceed the corresponding F statistic at the 95% level. In both cases we must reject the hypothesis that the multiplicative form of model is more powerful than the simpler linear form. Thus, for this sample of data a multiplicative form of model is not significantly more powerful than a linear form.
### Results of Hierarchical Regression Analysis

On the Sample of Raw Data

**Figure 5.21**

<table>
<thead>
<tr>
<th>FORM OF MODEL</th>
<th>( R^2 )</th>
<th>F RATIO</th>
<th>F-STAT (95%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>linear</td>
<td>0.5429</td>
<td>0.766</td>
<td>( F(3,373) = 2.64 )</td>
</tr>
<tr>
<td>two way interactions</td>
<td>0.5457</td>
<td>1.315</td>
<td>( F(1,372) = 3.86 )</td>
</tr>
<tr>
<td>two way interactions &amp; three way interaction</td>
<td>0.5473</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\( n = 304 \)

5.5.3 Discussion

It is possible that the true underlying relationship is more multiplicative than linear, but that for the range of data collected it is not possible to statistically differentiate the two. That is, we may be in somewhat the same position as a person in the middle of the Atlantic Ocean trying to determine whether the earth is flat or round. If all his measurements are gathered closely around his position, then it is only with exceedingly precise measurement that the curvature of the earth may be detected. Furthermore, for most problems within his vicinity, a flat earth model is perfectly adequate.

We have been able to reject the hypothesis that a multiplicative model of monitoring value provides a significantly better fit to the data than a linear model of monitoring value. That is not to say that the linear model is better, but only that the multiplicative model is not significantly better than the linear model.

There is a benefit to this finding. Just as the flat earth model simplifies many problems, such as surveying or traffic routing, a
linear causal model of monitoring value will simplify our analysis. There are more powerful statistical tools available for the analysis of linear models, than for the analysis of multiplicative models, and with our interval scale data it would not have been possible to convert our model to a linear form through logarithmic transformations. Thus, we have gained the use of linear analysis techniques, such as regression and linear causal modeling for further analysis.

5.6 Regression Analysis of the Monitoring Value Model

5.6.1 Analysis of the Monitoring Value Model Hypotheses

Regression provides one analytical approach for examining several of the hypotheses developed in the last chapter. It is a simple and widely used technique, but not without its weaknesses. In particular, regression analysis does not control for the attenuating effects of measurement error, especially in independent variables. In this section, we will examine the following hypotheses from the last chapter using regression analysis. In the next chapter, we will use structural equation models to provide further tests of these hypotheses.

**H1:** Information quality is a positively related determinant of monitoring value.

**H2:** When monitoring value is measured against the alternative of nonintervention, the probability of being out of control is a positively related determinant of monitoring value.
H4: When monitoring value is measured against the alternative of nonintervention, situation criticality is a positive determinant of monitoring value.

H6: When monitoring value is measured against a single alternative of either intervention or nonintervention, information quality (IQ), the probability of being out of control (PR), and situation criticality (CR) significantly predict MV.

The beta coefficients of a regression provide a measure of the significance of the effect of the independent variable upon the dependent variable. A t-test can be used to determine whether this relationship is statistically significant. Hypotheses H1, H2, and H4 can be tested in this manner. The statistical significance of the overall regression can be tested using an F-test and the practical significance of the regression model is indicated by the $R^2$ statistic. Hypothesis H6 can be tested with these two statistics.

5.6.2 Results

The results of the regression of CR, PR, and IQ on MV using the transformed data are shown in Figure 5.22. The overall regression is highly significant, as indicated by an F-ratio significant at the 99% level. From standard t-distribution tables we find that $t(304,.90) = 1.285$ and $t(304,.99) = 2.340$. Therefore, it is readily seen that the coefficient of the intercept is not significantly different from zero, even at the 90% level, and that the coefficient of each independent variable is significantly different from zero at the 99% level.

Thus, we may conclude that hypotheses H1, H2, H4, and H6 are
sustained by the regression analysis of the data. The regression model provides a statistically significant fit to the data and each of the three independent variables is a significant element of that model, having a positive influence upon monitoring value.

<table>
<thead>
<tr>
<th>TERM</th>
<th>COEFFICIENT</th>
<th>STD. ERROR</th>
<th>t-STATISTIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>intercept</td>
<td>1.485</td>
<td>3.265</td>
<td>0.455</td>
</tr>
<tr>
<td>CR</td>
<td>0.469</td>
<td>0.044</td>
<td>10.756</td>
</tr>
<tr>
<td>PR</td>
<td>0.373</td>
<td>0.041</td>
<td>9.174</td>
</tr>
<tr>
<td>IQ</td>
<td>0.134</td>
<td>0.040</td>
<td>3.383</td>
</tr>
</tbody>
</table>

\[ n = 304 \quad R^2 = 0.492 \quad F(3,300) = 96.8 \]

Linear Regression of CR, PR, and IQ on MV

**Figure 5.22**

5.6.3 Analysis of the Practical Significance of Each Factor

Another area of exploration is of the practical significance of each of the three independent variables as predictors of monitoring value. A total of 49.2% of the variation in monitoring value may be explained jointly by criticality, the likelihood that the situation needs intervention, and information quality. We would also like to know how each variable contributes to that predictive capability. As Figure 5.23 illustrates, three independent variables result in seven sources of predictive capability.
Sources of Prediction for Monitoring Value

Figure 5.23

In predicting monitoring value, the contribution of an independent variable to the fit of the model, the $R^2$, is not completely unique. For example, if CR was regressed on MV, the $R^2$ would be the result of the unique contribution of CR ($x_1$), the contribution made when either CR or PR is included ($x_4$), the contribution made when either CR or IQ is included ($x_5$), and the contribution made jointly by CR, PR, and IQ ($x_7$). In our diagram, $x_1$, $x_2$, and $x_3$ represent the unique contributions of CR, PR, and IQ, respectively. $x_4$, $x_5$, and $x_6$ represent contributions to the fit of the model that are obtained whenever one or both of the respective variables are included in the regression. For example, if PR and IQ was regressed on MV, the $R^2$ would equal the sum of $x_2$, $x_3$, $x_4$, $x_5$, $x_6$, and $x_7$. The only thing missing is the unique contribution of CR ($x_1$). Notice that we do not double count $x_6$. This contribution to the fit of the model is made when either or both IQ and PR are included in the regression. $x_7$ is
the contribution made whenever any of the three variables are included
in the regression.

These seven unknown values can be estimated by regressing MV on
all seven combinations of CR, IQ, and PR and solving the resulting set
of simultaneous linear equations. The initial tableau for this problem
is as follows:

\[
\begin{align*}
1 & 0 & 0 & 1 & 1 & 0 & 1 & X_1 & R_{CR} \\
0 & 1 & 0 & 1 & 0 & 1 & 1 & X_2 & R_{PR} \\
0 & 1 & 0 & 1 & 1 & 1 & 1 & X_3 & R_{IQ} \\
1 & 1 & 0 & 1 & 1 & 1 & 1 & X_4 & R_{CR,PR} \\
1 & 0 & 1 & 1 & 1 & 1 & 1 & X_5 & R_{CR,IQ} \\
0 & 1 & 1 & 1 & 1 & 1 & 1 & X_6 & R_{PR,IQ} \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & X_7 & R_{CR,PR,IQ} \\
\end{align*}
\]

where \( R_{CR,PR} \), for example, represents the \( R^2 \) statistic obtained
from the regression of CR and PR on MV.

5.6.4 Results

The \( R^2 \) statistics obtained from running each of the seven
possible regressions are shown in Figure 5.24.

\[
\begin{align*}
R_{CR} & = 0.331578 \\
R_{PR} & = 0.263302 \\
R_{IQ} & = 0.033919 \\
R_{CR,PR} & = 0.472428 \\
R_{CR,IQ} & = 0.349240 \\
R_{PR,IQ} & = 0.295839 \\
R_{CR,PR,IQ} & = 0.491815 \\
\end{align*}
\]

\( R^2 \) Statistics Obtained From Each Possible Regression

Figure 5.24

When these values were substituted into the simultaneous system
of equations (5.7), and solved, the following results were obtained:
Criticality alone explains 33.2% out of 49.2% of the explained variation in monitoring value. Volatility alone explains 26.3% and information quality alone explains only 3.4%. Criticality is the major determinant of monitoring value, both uniquely (19.6% predictive power) and jointly with volatility (11.8% predictive power). The likelihood of needing intervention is the next strongest determinant of monitoring value. Adding the PR term to a regression of CR on MV increases the explanatory power of the model by 14.3%. These results are consistent with earlier findings that criticality correlated most strongly with monitoring value and that the probable need for intervention correlated strongly with both monitoring value and criticality. Information quality is but a small determinant of monitoring value. Uniquely it accounted for only 1.8% of monitoring value variation. The rest of its power is accounted for jointly with criticality (1.3%).
5.6.5 Discussion

As tests in the last section indicated, each independent variable is a statistically significant determinant of monitoring value. Each regression coefficient was significantly different from zero. As well, the overall regression was highly significant. Across a large sample of data, each variable correlated well with monitoring value, and more highly with MV than with the other two independent variables. The conclusion to be reached is that there is empirical support for the statistical significance of each of the variables derived from our theoretical model of monitoring value.

Practical significance was also tested informally. No formal tests of practical significance are available. The major indicator of practical significance is the $R^2$ statistic. It provides an estimate of the amount of variation in the dependent variable explained by the independent variables. The $R^2$ of 0.492 obtained by regressing CR, PR, and IQ on MV indicates that much of the variation in monitoring value is explainable with our three independent variables. This has strong practical significance. The 50.8% variation left unaccounted is caused by error in measurement and incompleteness of our model. Regression analysis makes no corrections for the attenuating effects of measurement error. Therefore, it is not presently possible to determine how much of the unaccounted variation is due to either cause. In the next section, a technique is used that explicitly corrects for measurement error. This will allow us to assess the incompleteness of our model.

Analysis of the practical significance of individual variables was surprising. Results indicate that criticality and volatility are
both highly practically significant, but that information quality is not. Its unique contribution explains only 1.8% of the variation in monitoring value. Stated another way, dropping IQ from the full regression reduces the $R^2$ statistic from 49.2% to 47.4%. Statistically, this may be a significant change in $R^2$, but it is only a small decrease in the predictive power of the model.

Such a result indicates that the quality of information available to a manager has only a small effect upon the value the manager derives from monitoring that information. The perceived value is more a function of the criticality of the situation and of the probability that the situation is in need of attention. This result is logically a little puzzling. Our model and anecdotal evidence suggest that information quality should be perceived as an important practical determinant of the value obtained from monitoring. Without good quality information, one cannot properly assess whether to take corrective action.

We must be cautious not to overinterpret the results that have been obtained from these regression analyses. Without controlling for measurement error, estimates of parameters are not accurate; the proportion of variation in $MV$ explained by the model is not correctly estimated; and the partitioning of that variation among constructs is, at best, tentative. In the next section we will further explore the statistical and practical significance of each variable in our model of monitoring value using techniques that control for measurement error.
5.7 A Linear Causal Model of Monitoring Value

If variables are measured with error, then the randomness of the error tends to suppress the apparent relationship between variables. The effect is well known. Linear causal modeling is an analytic technique that allows us to analyze systems of linear model while controlling for measurement error. It is also a technique that is more flexible in the form of model that can be tested. This flexibility can be used to adjust a hypothesized model to take into consideration difficulties in measurement or changes in underlying theory.

5.7.1 The Model

Equation (5.2) provides a regression form for a linear model of monitoring value. For an analysis based on the covariance of measures, the intercept term can be disregarded and the equation can be rewritten in matrix form as follows.

\[
\begin{bmatrix}
MV \\
IQ \\
PR \\
CR
\end{bmatrix} = \begin{bmatrix}
\gamma_1 & 0 & 0 \\
0 & \gamma_2 & 0 \\
0 & 0 & \gamma_3
\end{bmatrix} \begin{bmatrix}
MV \\
IQ \\
PR \\
CR
\end{bmatrix} + \psi
\]

\[MV, IQ, PR,\text{ and } CR\text{ here are somewhat different than they have been used heretofore. In the regression model of the last section, they represented observed variates; now, they represent true variates. The distinction between true and observed variates is important if we are to model the effect of measurement error. The } \gamma_i \text{ terms are the weights for each of the independent variables. The } \psi \text{ term represents error. Monitoring value has been measured with three separate measures. The value obtained on each measure is a linear}
\]
combination of the effect of the underlying variable, MV, and measurement error. This can also be written in matrix form, with $Y_1$ representing the influence of MV on the value obtained by the measure MV and $\delta_1$ representing the error component.

\[
\begin{bmatrix}
MV_1 \\
MV_2 \\
MV_3
\end{bmatrix} = \begin{bmatrix}
Y_1 & 0 & 0 \\
0 & Y_2 & 0 \\
0 & 0 & Y_3
\end{bmatrix} \begin{bmatrix}
MV \\
\delta_2 \\
\delta_3
\end{bmatrix} + \begin{bmatrix}
\delta_1
\end{bmatrix}
\]

Similarly, three measurement submodels can be written for each of the three independent variables, IQ, PR, and CR.

\[
\begin{bmatrix}
IQ_1 \\
IQ_2 \\
IQ_3
\end{bmatrix} = \begin{bmatrix}
Y_{x1} & 0 & 0 \\
0 & Y_{x2} & 0 \\
0 & 0 & Y_{x3}
\end{bmatrix} \begin{bmatrix}
IQ \\
\delta_2 \\
\delta_3
\end{bmatrix} + \begin{bmatrix}
\theta_1
\end{bmatrix}
\]

\[
\begin{bmatrix}
PR_1 \\
PR_2 \\
PR_3
\end{bmatrix} = \begin{bmatrix}
Y_{x4} & 0 & 0 \\
0 & Y_{x5} & 0 \\
0 & 0 & Y_{x6}
\end{bmatrix} \begin{bmatrix}
PR \\
\delta_5 \\
\delta_6
\end{bmatrix} + \begin{bmatrix}
\theta_4
\end{bmatrix}
\]

\[
\begin{bmatrix}
CR_1 \\
CR_2
\end{bmatrix} = \begin{bmatrix}
Y_{x7} & 0 \\
0 & Y_{x8}
\end{bmatrix} \begin{bmatrix}
CR \\
\delta_7 \\
\delta_8
\end{bmatrix} + \begin{bmatrix}
\theta_1
\end{bmatrix}
\]

The system of equations represented by equation (5.8) to (5.12) is a linear causal model of monitoring value. It can be represented graphically and is shown in Figure 5.26.

5.7.2 Estimation and Testing of the Model

The estimation and testing of parameters for the model in Figure 5.26 was accomplished using the LISREL V statistical package. The fit of a model to the data can be assessed in several ways. The primary goodness of fit statistic computed by LISREL V is the chi-square statistic. It has degrees of freedom equal to the number of free elements in the measure covariance matrix minus the number of estimated parameters. The chi-square can be used to test the overall
A Causal Model of Monitoring Value

Figure 5.26
statistical significance of a hypothesized model against the alternative that the measures are arbitrarily correlated. If the chi-square statistic is large compared to the degrees of freedom, one rejects the estimated model as an accurate reflection of the system of underlying variables that generated the data.

The chi-square statistic summarizes a test of the proposed model against an alternative model of perfect fit. It is a direct function of sample size. This means that for larger samples, the statistic has a greater power to detect ill fitting models, even if the lack of fit is very small. For a sample size as large as ours (304), the estimated model can be rejected even if it accounts for 95% or more of the variation among the measures, because another model could additionally account for a portion of the residual variation. Bentler and Bonett[1980] observe:

As a consequence, in very large samples virtually all models that one might consider would have to be rejected as statistically untenable. Although the statistical conclusion is reasonable, namely, that the residual matrix may contain additional valuable information that a better model could in principle explain, the [estimated model] may contain virtually all of the information that one may be concerned with in practical circumstances.[p. 591]

Two other indicators of the fit of the model to the data are the standardized residuals for the estimated covariance matrix and the Q-plot of normalized residuals against normal quantiles. If a standardized residual is greater than two in value, then this is an indication that the model does not account very well for that covariation. The Q-plot may be interpreted as follows.

By visual inspection, fit a straight line to the plotted points. If the slope of this line is larger than
one, as compared with the 45 degree line, this is indicative of good fit. Slopes which are close to one correspond to moderate fits and slopes which are smaller than one to poor fits. [Joreskog and Sorbom, 1981, p. III.17]

A further indicator of goodness of fit is provided directly by LISREL V. The goodness of fit index (GFI) that we have previously used is "a measure of the relative amount of variance and covariances jointly accounted for by the model. Unlike chi-square, GFI is independent of sample size and relatively robust against departures from normality. Unfortunately, however, its statistical properties are unknown..." [Joreskog and Sorbom, p. I.41]

Bentler and Bonett[1980] propose another statistic, the incremental fit index (IFI), for assessing the practical significance of a hypothesized model. The index can be used to compare the hypothesized model to the most restricted model possible, where all \( \gamma \), \( \phi \), and \( \lambda \) parameters are set to zero. The IFI has an upper bound of unity and is a measure of the proportion of variation in the measure covariance matrix explained by the model under test.

If a model does not achieve good fit, additional parameters can be added to the model to account for problems in measurement or to adjust the tested theory. The difference in chi-square obtained between a base model and an additionally restrained model has degrees of freedom equal to the number of restraints added. Hence, the chi-square statistic can be used to test the significance of changes to a series of progressively more restrictive hypothesized models. The caution here, though, is that in using the modification indices, the process moves from confirmatory analysis to exploratory analysis. Cliff observes, ". . . once one starts adjusting a model in the light
of the data, the model loses its status as a hypothesis, and that model finally chosen represents in practice a much more unstable picture of what is really going on."[Cliff 1983, p. 124]

Some confirmation of revised models can be provided by cross-validation. Cliff continues:

One can split the original sample in half, and put one half aside. Fiddle with models to one's heart's content on the first half. When one has a model that seems to fit, bring out the other half of the data, and try that model out on it. As far as those data are concerned, the model is a legitimate hypothesis - those data did not influence the nature of the model. If the model fits, everything is satisfactory . . .[Cliff 1983, p. 124]

Even further confirmation can be provided by testing for equivalence of parameter estimates across the two samples. If a single set of estimates provides an acceptable fit to the two samples of data, then this provides some evidence that the modifications are not unique to the data exploration.

5.7.3 Results of Estimation and Testing

The standard estimates of the model parameters are shown in Figure 5.27. All parameter estimates are statistically significant. The two intercorrelations between IQ and PR and between IQ and CR are significant at the 0.05 level; all other estimates are significant at the 0.01 level. The standardized psi estimate of 0.28 indicates that 72% of the variation in the dependent construct was accounted for by variation in the three independent constructs. This is greater than the 49.2% of variation in monitoring value explained by the simple regression in the last section because the effects of measurement error have been controlled. Of the three independent constructs, situation
criticality was the most important, with a standardized weight of 0.593. The next most important construct was the likelihood of being out of control, with a weight of 0.394. These two constructs are moderately correlated (\(\phi = 0.340\)). The third construct, information quality is not an important predictor of the value of monitoring. It covaried about equally with each of the other three constructs. These results are consistent with the findings of the regression analysis in the last section.

The overall chi-square statistic for this model was 
\[ \chi^2(36) = 96.09, p = 0.000. \]
This is an indication that some significant amount of variation in the measure covariance matrix remains unexplained by the model. An examination of the standardized residuals provides confirmation. Of the 66 standardized residuals, two have values greater than 2 (MV1,CR1 = 2.4; MV3,IQ1 = 2.2). These were two pairs of measures for which error terms had to covary to achieve a statistically significant fit for the model of discriminant validity.

There is evidence that the overall fit of the model, while not statistically significant, is also not terrible. The chi-square statistic is only about two and one half times the degrees of freedom; most of the residuals are low in value; and the Q-plot indicates that the model has achieved a moderate fit to the data. The slope of the plot, about 1.1, is somewhat greater than one.

Some indication of the practical significance of the model has already been provided by the estimate of psi. A model that explains more than seventy percent of the variation in the dependent variable has important practical implications. Two other indications of practical significance are provided by the goodness of fit index and by
Bentler and Bonett's incremental fit index. These indices achieved values of GFI = 0.928 and IFI = 0.935. The measures are consistent and indicate that about 93% of the variation in all measures can be accounted for by the model. Any other model could improve the overall fit to the data by no more than 7%. But, it is precisely because another model could explain some of that seven percent variation that the model did not achieve overall statistical significance.

<table>
<thead>
<tr>
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<th>GAMMA</th>
</tr>
</thead>
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<tr>
<td></td>
<td></td>
<td>PR</td>
</tr>
<tr>
<td>MV</td>
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<td>0.394 (0.064)</td>
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<table>
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<td></td>
<td>PR</td>
</tr>
<tr>
<td>IQ</td>
<td>1.000 (0.121)</td>
<td></td>
</tr>
<tr>
<td>PR</td>
<td>0.129 (0.071)</td>
<td>1.000 (0.114)</td>
</tr>
<tr>
<td>CR</td>
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<td>0.340 (0.083)</td>
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<tr>
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<table>
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<tbody>
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<td></td>
<td>MV1</td>
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<td>16.497 (0.00)</td>
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<tbody>
<tr>
<td></td>
<td></td>
<td>PR</td>
</tr>
<tr>
<td>I1</td>
<td>20.028 (1.45)</td>
<td>-3.815 (1.12)</td>
</tr>
<tr>
<td>I2</td>
<td>24.611 (0.00)</td>
<td>0.000 (0.00)</td>
</tr>
<tr>
<td>I3</td>
<td>19.902 (1.50)</td>
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<tr>
<td>PR2</td>
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<tr>
<td>CR1</td>
<td>0.000 (0.00)</td>
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</tr>
<tr>
<td>CR2</td>
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n = 304

Estimates and Standard Errors for Model of Monitoring Value in Figure 5.27

Figure 5.27
5.7.4 Modifications to the Model

The insignificant chi-square statistic achieved across the entire sample of 304 situations led us to explore modifications to the model that would improve the fit. To this end, the sample of data was broken into two equal parts by ordering the situations according to a randomly assigned number and splitting the sample at the midpoint. We will refer to the two samples as A and B.

The standardized residuals obtained from the previous test indicated that the covariations between dependent and independent measures were not adequately estimated by the model. To allow covariation among these measures, the model was redefined in equivalent terms. We will continue to report the results for the original form of the model.

The model in Figure 5.26 was reestimated using the data from sample A. The standardized estimates are provided in Figure 5.28. Three parameter estimates failed to achieve statistical significance. The two intercorrelations between IQ and PR and between IQ and CR, which achieved statistical significance across the sample of 304 situations, are not significant in sample A. This appears to be a direct result of reduced sample size, since the estimates are both larger for sample A. The gamma weight of the effect of IQ on MV is nonsignificant. This is disconfirming evidence for hypothesis H1, that information quality is a significant positive determinant of monitoring value. All other estimates are significant at the 0.01 level and approximately equal to the previous estimates.

The overall chi-square statistic for this model was
\( \chi^2(36) = 65.40, p = 0.002 \). The decrease of more than thirty points in the chi-square statistic is an indication of its sensitivity to sample size. But, a significant amount of variation in the measure covariance matrix remains unexplained by the model. The goodness of fit index and Bentler and Bonett's incremental fit index achieved values of \( \text{GFI} = 0.889 \) and \( \text{IFI} = 0.936 \). While the statistical significance of the model has increased, the practical significance has dropped slightly. The power of the model to predict monitoring value can be observed to have increased slightly to 73.7\%. 
The modification indices provided by the LISREL V program indicated two successive changes that would improve the fit of the model. The first is to allow the error terms of the measures MV1 and CR1 to covary. The second is to allow the error terms of the measures MV3 and IQ1 to covary. These correspond to the significant standardized residuals obtained from the estimate of the model across
the entire sample. The standardized estimates of the revised model are shown in Figure 5.29. The chi-square statistic for this model is $\chi^2(34) = 46.73$, $p = 0.072$. The model provides a satisfactory fit to the data. The goodness of fit indicator and the incremental fit index have the values, GFI = 0.916 and IFI = 0.971. Therefore, this model achieves both statistical and practical significance.

<table>
<thead>
<tr>
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<th>CR</th>
</tr>
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<tbody>
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<td>0.578 (0.104)</td>
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<tbody>
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<td></td>
<td></td>
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<tr>
<td>PR</td>
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<td>CR</td>
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<td>1.000 (0.292)</td>
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<table>
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<th>LAMBDA Y</th>
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<tbody>
<tr>
<td>MV1</td>
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<tbody>
<tr>
<td>IQ1</td>
</tr>
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</tr>
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<td>24.498 (0.00)</td>
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</tr>
<tr>
<td>17.375 (2.97)</td>
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<td>12.900 (0.00)</td>
</tr>
<tr>
<td>22.947 (2.30)</td>
<td>0.000 (0.00)</td>
<td>23.849 (4.39)</td>
<td>0.000 (0.00)</td>
</tr>
</tbody>
</table>

$n = 152$

Estimates and Standard Errors for the Revised Model of Monitoring Value in Figure 5.27 Using Split Sample A

Figure 5.29
5.7.5 Tests of the Revised Model

In the last section, we allowed the data to guide us toward variations in the model that improved the overall fit. These modifications resulted in a statistically significant improvement in the fit of the model and a small improvement in the practical significance of the model.

In this section we reanalyze the modified model using the holdout sample B. This achieves two purposes. First, it provides a confirmatory test of the results of the data exploration. If modifications of the model are peculiar to the covariance structure of the data sample, rather than to the underlying theoretical variables, then the revised model would not provide a good fit to the data in sample B. The second purpose that a random split sample analysis fulfills is as a further test of the statistical significance of the modified model. We can test whether the two sets of estimated parameters are significantly different. If the two models estimated from the two sample halves are not statistically different, then this confirms that the modified model is representative of the underlying phenomenon.

We can provide five tests of the hypothesis that the revised model of monitoring value represents the true relationships between the four constructs under examination. These correspond to the following test hypotheses.

T1: The revised monitoring value model provides a significant fit to the holdout sample data.
T2: When the construct loadings (gammas) are constrained to be equal across the two samples, the model provides a significant fit to the data.

T3: When the construct loadings and intercorrelations (phis) are constrained to be equal across the two samples, the model provides a significant fit to the data.

T4: When the construct loadings, intercorrelations and measure weights (lambdas) are constrained to be equal across the two samples, the model provides a significant fit to the data.

T5: When the construct loadings, intercorrelations, measure weights, and error variances (thetas) are constrained to be equal across samples, the model provides a significant fit to the data.

The revised model from the last section was reestimated using the data from sample B. The standardized estimates are provided in Figure 5.30. The overall chi-square statistic for this model was \( \chi^2(34) = 40.31, p = 0.211 \). This sustains test hypothesis T1. The practical significance indicators for this model were GFI = 0.933 and IFI = 0.985.

The results of separate tests of hypotheses T2 through T5 are provided in Figures 5.31 and 5.32. Two tests of each hypothesis were made. A weak test was made by examining the concurrent fit of the model to the two samples of data, under the constraint that the appropriate factors are invariant across samples. If the model with invariant parameters does not fit the data, then this is disconfirming evidence of the equality of parameters across the two samples. The results of these tests are shown in Figure 5.31. In all cases, the hypotheses were sustained. There was no evidence that the model
estimates were unequal across the two samples.

A second and stronger test of the hypotheses was made by examining the difference in chi-square and degrees of freedom between each of the models reported in Figure 5.31 and the base model, in which the model was concurrently fit to the two samples of data without any constraints between the models. This difference is a chi-square statistic of the significance of the invariance constraints. If the addition of invariance constraints reduces the fit of the model an insignificant amount, then the hypothesis of equal corresponding parameters across the two samples may not be rejected. The results of these tests are shown in Figure 5.32. In all cases the addition of invariance constraints reduces the fit of the model insignificantly. Therefore, all test hypotheses are sustained.
Estimates and Standard Errors for the Revised Model of Monitoring Value in Figure 5.27 Using Holdout Sample B

Figure 5.30
Summary of Split Half Sample Fit To Various Constrained Models

<table>
<thead>
<tr>
<th>TEST HYPOTHESIS</th>
<th>CHI-SQUARE</th>
<th>DEGREES OF FREEDOM</th>
<th>P-VALUE</th>
<th>DECISION</th>
</tr>
</thead>
<tbody>
<tr>
<td>T2</td>
<td>88.58</td>
<td>71</td>
<td>0.077</td>
<td>accept</td>
</tr>
<tr>
<td>T3</td>
<td>92.75</td>
<td>78</td>
<td>0.122</td>
<td>accept</td>
</tr>
<tr>
<td>T4</td>
<td>94.76</td>
<td>87</td>
<td>0.267</td>
<td>accept</td>
</tr>
<tr>
<td>T5</td>
<td>106.47</td>
<td>100</td>
<td>0.93</td>
<td>accept</td>
</tr>
</tbody>
</table>

Summary of Split Half Sample Test Results

<table>
<thead>
<tr>
<th>TEST HYPOTHESIS</th>
<th>CHI-SQUARE</th>
<th>DEGREES OF FREEDOM</th>
<th>P-VALUE</th>
<th>DECISION</th>
</tr>
</thead>
<tbody>
<tr>
<td>T2</td>
<td>1.54</td>
<td>3</td>
<td>0.69</td>
<td>accept</td>
</tr>
<tr>
<td>T3</td>
<td>5.71</td>
<td>10</td>
<td>0.80</td>
<td>accept</td>
</tr>
<tr>
<td>T4</td>
<td>7.72</td>
<td>19</td>
<td>0.99</td>
<td>accept</td>
</tr>
<tr>
<td>T5</td>
<td>19.43</td>
<td>32</td>
<td>0.93</td>
<td>accept</td>
</tr>
</tbody>
</table>

5.7.6 Conclusions on the Linear Causal Model of Monitoring Value

The linear causal modeling analysis provided a more powerful approach to analyzing the monitoring value model in a linear form. It allowed for direct control of random measurement error and provided a modeling flexibility that allowed for modifications to adjust for measurement problems. We were able to test both the statistical and practical significance of the monitoring value model. The statistical significance of the original model was not achieved. Part of the difficulty was caused by the relatively large sample size, for it made even slight misfits between the data and the estimated model
statistically significant. The majority of the difficulty, though was due to two measure covariances that were inadequately explained by the model. When these measures' error variances were allowed to covary, a statistically significant fit was achieved.

A test of this revised model was made against a holdout sample of 152 situations. The results sustained the model. It provided a good fit to the data and when the two split sample were used to jointly estimate the model, under constraints of parameter equalities, a statistically significant fit was obtained.

The practical significance of the monitoring value model was quite high across all models. More than 90% of the variation among measures could be explained with the three independent variables. For the original monitoring value model, the three independent constructs were able to explain more than 70% of the variation in monitoring value. The majority of this explanatory power was provided by the situation criticality construct. For the revised model, the explained variation in the dependent variable dropped. For sample A, 70.7% of the variation was explained and for sample B, 62.6% was explained by the three independent constructs. The decline in explanatory power is attributable to the nature of the revisions made to the model. Both changes implied some undetected latent variable was responsible for some of the covariation between two dependent and independent measures. They "took away from" the explanatory power of the model.

Each of the estimated models indicate that situation criticality plays a dominant role in determining the perceived value of monitoring a situation. The likelihood of being in need of intervention plays a moderate role, though some of its effect could be reflected through the
criticality construct since these two are correlated at about the 0.3 level. Information quality was only borderline statistically significant and insignificant in a practical sense.

5.8 Discussion

This empirical investigation of the model of monitoring value has obtained results in five areas. We have examined the reliability and validity of a new measurement instrument and tested the multiplicative form of the model, the statistical significance of a linear form of the model, the practical significance of a linear model, and the practical significance of each variable in the model. In this section, we shall discuss the implications of the results and suggest some further lines of inquiry.

The measurement instrument employed passed the standard tests of reliability and validity with minor violations. By traditional standards the instrument is of good quality. Further analysis using linear causal modeling revealed other difficulties with the instrument. In particular, one measure of the likelihood of needing intervention and another of information quality loaded on each other's construct. In both cases, the response was influenced not solely by the construct that was intended to be measured, but also by the other, related construct. For example, one question asked about the probability that the situation needs intervention. Responses were influenced not just by the latent need for intervention, but also by the respondent's uncertainty about the condition of the situation. This latter variable is closely related to the information quality construct. To improve
the measurement instrument, these two questions should be modified so that any ambiguity as to the cause of the response is eliminated. Each measure should measure a single construct.

Two other minor measurement problems were overcome in the split sample analysis. One measure of information quality and another of criticality were found to covary with separate measures of monitoring value, even after the effects of the structural model were removed. These unexplained covariations were probably due to methods bias that would not recur on the next implementation of the survey instrument.

Across the total sample of data collected, support was not found for the multiplicative form of the monitoring value model. Three possible explanations suggest themselves. It may be that (1) the underlying constructs do not combine in a multiplicative fashion, or (2) measurement error and (3) the narrow range of sampled data, reduced the power of the test to discern the superior fit of the multiplicative model over the linear model. There is a need to further test the form of the monitoring value model. Two different approaches could be used. One is to redesign the measurement instrument so that it collects ratio scale data. Then direct comparisons of fit of a log-linear and a linear model of monitoring value can be made. The problem with this approach is that the development of an instrument for collecting ratio scale data is quite difficult and the final instrument may introduce measurement error more costly than the benefits of ratio scale data. A second approach is to use the present instrument, or its revised version, to collect data across a wider range of situations. This could be accomplished by asking the respondent for data on specific situations pre-selected to display a wide range of data values.
Regression analysis of the linear model of monitoring value revealed that the overall fit of the model is statistically significant and that each of the independent variables is statistically significant. As predicted by the model of monitoring value, criticality, the probability of being out of control, and information quality are all significant determinants of monitoring value. When the data was further analyzed using linear causal modeling, a slightly revised structural model of monitoring value achieved statistical and practical significance.

The model that we derived in the last chapter and tested here is based upon an analysis of economic models of monitoring value. Each of the constructs that we have included is present in those theoretical models, yet our simplified model is not a complete reflection of those models. It appears, though, that the simplified model provides a good practical substitute for those models. It explains the value obtained from monitoring a situation with about seventy percent accuracy. This exceeds the accuracy obtained in recent tests of economic information value models [Schepanski and Uecker 1983], which closely parallel economic models of monitoring value.

The practical significance of each particular independent variable was found to vary widely. Criticality is the dominant determinant of monitoring value. The likelihood of needing intervention in the next most important, and information quality provides very little additional predictive power. It has little practical significance.

This result is at odds with intuition, which holds that the quality of one's sources of information is an important determinant of
the value one obtains from monitoring a situation. It is also at odds with other empirical tests of the relationship between information quality and perceived value. [Hilton 1979; Wilson 1975; Ijiri and Itami 1973] There are three possible explanations for the empirical finding: (1) for the task of monitoring, information quality doesn't affect monitoring value greatly, (2) the result is peculiar to the sample, or (3) respondents were incorrectly assessing the quality of available information. For example, although measures asked for assessments of both formal and informal sources of information, respondents may have assessed only their formal information sources. Further testing can determine which of these explanations is correct. The revised instrument should contain separate measures of formal and informal sources of information and be administered to a wide sample of respondents. Each explanation of the phenomenon can then be tested.

The importance of criticality as a determinant of monitoring value should also be submitted to further testing. Criticality and the likelihood of needing intervention were found to correlate at about the 0.3 level. It is possible that respondents were confounding these two constructs, that managers were rating a situation as critical because it was perceived to be volatile. Refinements to the measurement instrument would allow us to test for such effects.

The consistent recommendation of this discussion is for more testing. In testing people's perceptions about situations, information sources, and value a study like this is bound to raise more questions than it can answer. Much further study is needed.
6 DISCUSSION AND SUMMARY

6.1 Introduction

This thesis has developed a simplified model of the value of monitoring. It has embedded the model in a new technique for analyzing information needs for monitoring. It has developed an instrument for measuring the variables in the monitoring value model, and it has applied that instrument in a field setting. Analysis of the results indicates that the monitoring value model is very satisfactory. The three independent variables, situation criticality, the likelihood of needing intervention, and information quality predict the value one obtains from monitoring a particular situation with good accuracy.

In this chapter, we will explore the implications of these results for other related topics in MIS. Specifically, these results bear directly upon the theoretical and empirical validity of the critical success factors method. As well, they have implications for a new approach to planning and prioritizing management information systems development. This will also be discussed.

As with most research, this work has raised more questions than it has answered. Several follow on studies suggest themselves for the monitoring value model. These shall also be discussed in this chapter.
6.2 Implications for the New IRA Technique

In chapter four, we developed a simplified model of the value of monitoring and discussed its use in a new technique for information requirements analysis for monitoring. The new technique was to be similar in implementation to the critical success factors technique. A manager would work with an expert to determine his objectives and associated measures and to develop a pool of prospective situations that relate to those objectives. For each of these situations, measures were to be made of situation criticality, available information quality, and the average probability that the situation will need attention. With each of these measures in hand, the value of monitoring each situation could be estimated as the product of the scores on each of the three factors. The situations with the highest estimate of monitoring value would be selected for monitoring.

The work in the last chapter has sustained the simple monitoring model that underlies such a technique, but it has also provided empirical evidence for how the technique could be streamlined and improved. One conclusion of the empirical analysis was that the information quality construct had little effect upon the value of monitoring. Its practical contribution to the predictive power of the model was quite low. For our technique, the effort expended in obtaining measures of information quality would not be worthwhile. Therefore, on the basis of the empirical evidence, we can use only situation criticality and the likelihood of needing intervention to determine which situations to monitor.

Based on the simplified monitoring value model, our new technique
proposed to multiply factor scores together to arrive at an estimate of monitoring attractiveness. There is no empirical support for the proposition that a multiplicative monitoring value model is superior to a linear form. Therefore, it is not necessary that the estimate of monitoring attractiveness be formed as a product of factors; an additive estimate will do just as well. Given this, a further modification of the new technique suggests itself. Instead of developing a pool of situations which are then scored on the two remaining factors, one could combine the search and evaluation processes into a single iterative procedure. Once the manager and expert have developed the set of objectives and measures, they proceed along the lines of the CSF method to identify situations that are critical to meeting those objectives and have some probability of needing intervention. They then turn their attention toward identifying those situations that are likely to need intervention, to go out of control, and have at least moderate importance. These two sets contain the situations of interest: those that are critical and those that will likely need intervention. These sets can be joined and situations can be removed if the combination of criticality and intervention probability doesn't appear to make it a worthwhile candidate for monitoring.

6.3 A Revised Critical Success Factors Method

The efforts of this thesis have provided a method for how to determine information requirements for monitoring. The new method is related both theoretically and empirically to Rockart's critical
success factors method. With insights gained from the empirical analysis of the monitoring value model, we have suggested changes to the new technique that result not so much in a new technique as in a revision of the CSF method. Combined with a practically proven method that has already gained wide recognition and use, the insights gained from this present work are multiplied.

According to the critical success factors method, the situations most worth monitoring and the situations for which information systems should be provided, are those that are most critical. According to the new technique, the situations most worth monitoring are those for which some implicitly determined combination of situation criticality and the probability of needing intervention is largest.

Situation criticality is one of the most important factors that determines how worthwhile it is to monitor a situation. This empirical fact is supported by the analysis in this thesis and is the basis for the CSF method. Our analysis also found that the likelihood that a situation will need intervention is another factor that affects the value of monitoring a situation. Its influence is not as great as that of situation criticality, but its inclusion in a model of monitoring value significantly improves the predictive accuracy of the model. Therefore, its inclusion in a technique for determining information requirements may also be helpful.

This change to the CSF method would not be without expense. The addition of another dimension for consideration could impair the versatility of the method. By staying simple, the CSF technique has found uses in a wide variety of problems. It is used not just to determine which situations are worth monitoring or worth building
information systems for, but also as a stimulus to creative strategic
tinking. It is used for prioritizing information systems development
and as a diagnostic aid of management style. When a manager reveals
his critical success factors, he is revealing something about the way
he sees his world, his job, and himself. In the next few sections, we
will briefly explore the use of the revised CSF technique in some of
these areas.

6.4 Information Systems Planning

One of the original use of the critical success factors method
was as a tool that helped determine the need for improved information
systems. Those situations that were most critical were those for which
improved information was recommended. The value of monitoring model
can lend some insight into this problem of prioritizing information
systems development. Let us first consider the original model

\[ MV = CR \times PR \times IQ \]  

(7.1)

where CR, PR, and IQ represent situation criticality, probable need of
intervention, and information quality, respectively.

In planning information systems improvements, one contemplates
increasing the quality of available information. Generally there is an
upper bound on the improvements that can be made at an affordable cost.
The effect of such improvements can be represented by IQ. If we
represent the cost of the information systems improvements by K, then
equation 7.1 allows us to predict the net value of the information
systems improvements.
For which situations should information quality be improved?

Equation 7.2 suggests that it is not necessarily for those which are most critical, but rather for those for which the improvement in information systems quality results in the largest net gain in monitoring value. Thus, even though a situation is less critical, the opportunity for a large and inexpensive gain in information quality may make it a more attractive candidate for a new information system than a critical situation for which good information is already available, or for which good information is expensive to obtain.

But, then the empirical evidence must be taken into consideration. That evidence suggests that information quality has little impact upon the value obtained from monitoring. Information systems for monitoring don't matter that much. This is consistent with the observations of Mintzberg. His study of five chief executives led him to conclude that in monitoring their organization, senior managers obtained very little value from their formal information systems. Thus, improvements in such systems may provide proportionally little value.

6.5 Uses and Extensions for the Monitoring Value Model

The new technique for information requirements analysis for monitoring represented one use of the value of monitoring model. Information systems planning provided a setting where an extension to the model provided new insights to a specialized problem. There are
several other uses that can be made of the model and many more extensions that can increase the monitoring value model's use to even more problems. Each of these new uses and extensions constitutes an opportunity for follow on studies. In this section, we explore some of these directions for future research that suggest themselves from this present work.

6.5.1 Diagnosis of Management Style: The information needs analysis application of the monitoring value model was an example where the model was used to diagnose individual situations. It can also be used to diagnose management style and ability. In the data gathered for the empirical study, there was evidence that individuals varied significantly in the relative weights with which each of the three independent variables determined monitoring value. There were those individuals whose perceptions of monitoring value were related most strongly to the likelihood that the situation would need intervention. These individuals tended to have operational roles, such as manager of production. Their focus was upon short term problem solving and they perceived that the most value was obtained when they were responding to problems with situations.

There were also managers who tended to have relatively heavy weightings on situation criticality as a determinant of the value of monitoring. These people tended to be senior managers and planners. Their time perspective was longer than that of the first group. They were more concerned with the larger picture than they were with the details of problems. There were also a relatively small group of managers whose perception of the value of monitoring was heavily
influenced by the quality of information they had available. This is
that the relative importance of situation criticality, volatility, and
information quality is somehow related to the style and role of the
individual manager. The evidence is circumstantial and anecdotal. It
demands further exploration.

As well as variation in the relative weightings of independent
variables across individuals, there was significant variation in the
overall predictive power of the independent variables from individual
to individual. This is important, for the monitoring value model
explicitly included assumptions about the rationality of the manager.
If the ability of the manager to monitor is low, then he violates
rationality assumptions and the fit of the model, the predictive power
of the independent variables, would be lower. So perhaps the
predictive power of the model applied to an manager's set of situations
is a measure of the manager's monitoring ability. Here we are clearly
on untested ground, for the variation is also attributable to variation
in measurement error across individuals. The differences in fit across
individuals may just be due to the fact that some managers might have
understood the measurement instrument better than others.
Nevertheless, the possibilities are intriguing.

6.5.2 Diagnosis of Situation Types: The monitoring value model can
also be used to diagnose characteristics of types of situations. If
situations are characterized as either operational or strategic in
nature, then one could develop a priori hypotheses about the relative
importance of situation criticality and the likelihood of needing
intervention as determinants of monitoring value, for these two groups.
One might expect that in the strategic set of situations, criticality would be a relatively more important predictor of the value of monitoring. That is, situation criticality more strongly differentiates the value a manager obtains from monitoring a set of strategic situations than does the likelihood that the situation needs intervention. For operational situations, one might expect the opposite result to obtain. Again, this is just conjecture, but there was some circumstantial support found in the data gathered for the empirical study.

6.5.3 Refinements to the Model: There are also opportunities for developing a more refined model of monitoring value. To provide a greater detail of understanding of the value of monitoring, each of the independent variables could be modeled by a set of subvariables and these related to the value of monitoring. Consider situation criticality. It is defined as the difference in value between the situation being in good shape and in bad shape. This difference is the sum of the direct and indirect consequences of the situation falling into poor condition. For example, if a drop in earnings from twenty million dollars to nineteen and a half million dollars violates an important loan covenant, then the direct consequence of a drop of one half million dollars may be overshadowed by the indirect effect of an abrogated loan agreement. The earnings situation might be quite critical because of its impact on the condition of another situation. Thus, criticality might be modeled as the sum of two types of consequences and the indirect consequences modeled as a function of the interdependence of a situation with other situations and the
criticality of those related items.

In the present monitoring value model, the available information is grossly characterized by a variable called information quality. There are several subvariables that determine the quality of available information. Timeliness, reliability, availability, accuracy, level of detail, are but a few drawn from the MIS literature. If the model could be constructed relating these characteristics of information to perceptions of overall quality, then it could be embedded in a more detailed model of monitoring value. Now it would be possible to relate changes in the timeliness or accuracy of monitoring information to the value of that improvement. This capability is presently missing from the MIS field. Theoretically grounded, yet practically useful models do not exist to relate characteristics of information to its value.

The development of a monitoring value model at the next level of detail opens several new opportunities for its use. For example, if the criticality of a situation is partly a function of how closely it is coupled to other situations, then the effects of decoupling situations, through standard operating procedures or organizational slack, could be examined with this more detailed model. One could trace the impact of decoupling a situation using an extension to the model similar to that used for information systems planning.

Many more possibilities for extensions to the use and form of the model could be suggested. The variety of opportunities stems from the fact that the model is informative on a fundamental managerial activity, monitoring. This was an initial intuition for choosing monitoring as the process to be modeled.
REFERENCES


APPENDIX A

QUESTIONNAIRE
Managers and Monitoring: A Questionnaire
concerning the attributes of situations
that managers monitor.

In the course of a business day, the typical manager receives information on many different situations that affect his or her work. A budget report may indicate that the manager is doing well against plan, the habitual late arrival of an employee may signal a personnel problem, or discussions with a customer may indicate difficulties with quality control. These situations that interest particular managers vary widely in degree of detail, need for timely attention, and importance.

Managers rely upon hundreds of sources of information, both formal and informal, to monitor these situations. Often there is not a shortage of relevant information for monitoring, but an overabundance of irrelevant signals and data that serve to obscure the most critical information. Techniques have been developed to identify which situations are most important for a manager to monitor and, therefore, which situations deserve special attention for information systems development.

In this study we are exploring the attributes of situations that make them more or less important for managers to monitor. From literature on the economics of information value, we have developed a model of what we believe are the key attributes of important situations. The questionnaire will be the basis of an empirical study that will accept, reject, or modify that model. If we can determine the ingredients of situation importance, then we can also use the knowledge to validate, improve, or reject existing techniques which are in widespread use in organizations today.

Please read each question carefully and answer each without reference to previous questions. Although some questions may appear similar, they are all asking slightly different things. The differences are quite important to this study.

If you wish to comment on any questions, please feel free to use the space in the margins. Your comments will be read and taken into account.

Thank you for your help.

Michael Treacy
Sloan School of Management
M.I.T.
Please indicate, in any order, ten situations that you routinely monitor.

#1

#2

#3

#4

#5

#6

#7

#8

#9

#10
Using the following scale, please indicate for each situation your degree of concern at being told by a trusted peer, "We've just discovered a major difficulty with situation X."

| very concerned |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               |               | mea
Using the following scale, please indicate the amount of information you usually have available to monitor each situation.

<table>
<thead>
<tr>
<th>Situation #1</th>
<th>Situation #2</th>
<th>Situation #3</th>
<th>Situation #4</th>
<th>Situation #5</th>
<th>Situation #6</th>
<th>Situation #7</th>
<th>Situation #8</th>
<th>Situation #9</th>
<th>Situation #10</th>
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</table>
Using the following scale, please indicate for each situation the probability that the situation will need some significant managerial action on your part during the next six months.

<table>
<thead>
<tr>
<th>Certainty</th>
<th>about 50-50</th>
<th>No possibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Situation #1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation #2</td>
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<td></td>
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<tr>
<td>Situation #3</td>
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<tr>
<td>Situation #4</td>
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<td>Situation #6</td>
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<td>Situation #7</td>
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<td>Situation #8</td>
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<td></td>
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<tr>
<td>Situation #9</td>
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<tr>
<td>Situation #10</td>
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</tbody>
</table>
The value of monitoring is obtained through corrective or opportunistic managerial intervention that would not have been taken if a situation had not been monitored.

Using the following scale, please indicate for each situation the value you expect to receive, during the next year, from monitoring that situation.

<table>
<thead>
<tr>
<th>of very little value</th>
<th>of moderate value</th>
<th>extremely valuable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Situation #1</td>
<td></td>
<td></td>
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<td>Situation #2</td>
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<td>Situation #9</td>
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<tr>
<td>Situation #10</td>
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</tbody>
</table>
Assume for the moment that every situation is in serious need of attention.

For which situation would your corrective actions yield the most valuable improvement?

For which situation would your corrective actions yield the least valuable improvement?

Using these situations as endpoints on the following scale, please indicate the relative value of corrective actions in response to the need for attention to each situation. Indications may be made by placing the situations' numbers on the scale at the appropriate positions.
Situations may be tracked using information from several sources. Accounting reports and analyses, views and opinions of colleagues, rumor, and discussions with customers, suppliers, and competitors may all be used to form a more complete picture of the condition of any situation.

With all the information sources you presently use, on which situation do you usually have the most complete information as to the condition of the situation?

With all the information sources you presently use, on which situation do you usually have the least complete information as to the condition of the situation?

Using these situations as endpoints on the following scale, please indicate the relative completeness of the present information sources for each situation. Indications may be made by placing the situations' numbers on the scale at the appropriate positions.

situation with the least complete information

situation with the most complete information
Using the following scale, please indicate for each situation the probability that the condition of the situation presently warrants some type of major managerial action on your part.

<table>
<thead>
<tr>
<th>Situation #1</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Situation #2</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Situation #3</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Situation #4</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Situation #5</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Situation #6</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Situation #7</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Situation #8</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Situation #9</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Situation #10</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
</tr>
</tbody>
</table>
At this moment, which situation is **most important** to your success as a manager?

At this moment, which situation is **least important** to your success as a manager?

Using these situations as endpoints on the following scale, please indicate the relative importance, at this moment, of each of the other situations. Indications may be made by placing the situations' numbers on the scale at the appropriate positions.

---

#_____  #_____  

**most important situation**  **least important situation**
Situations may be monitored both through formal monitoring and reporting systems and more casually through informal means. For example, sometimes monitoring is simply an involuntary act, resulting in an awareness of the present condition of a situation.

During the past six months, for which situation have you found monitoring, both formal and informal, to yield the greatest value?

#_______

During the past six months, for which situation have you found monitoring, both formal and informal, to yield the smallest value?

#_______

Using these situations as endpoints on the following scale, please indicate the relative value that your monitoring of each has yielded. Indications may be made by placing the situations' numbers on the scale at the appropriate positions.

#__________

situation for which monitoring has yielded the greatest value

#__________

situation for which monitoring has yielded the smallest value
Assume, for the moment, that you have just reviewed all of your formal and informal sources of information for each situation. Please indicate on the following scales the degree to which you would still be uncertain about the exact status of each situation.

<table>
<thead>
<tr>
<th>completely uncertain about its status</th>
<th>about 50% certain about its status</th>
<th>completely certain about its status</th>
</tr>
</thead>
<tbody>
<tr>
<td>Situation #1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation #2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation #3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation #4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation #5</td>
<td></td>
<td></td>
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<tr>
<td>Situation #6</td>
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<td></td>
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<tr>
<td>Situation #7</td>
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<tr>
<td>Situation #8</td>
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<tr>
<td>Situation #9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation #10</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Assume you are placed in a dark room with no access to the outside world, except for food and water, today.

When you come out three months later, which situation would you want to know about most?

When you come out three months later, which situation would you want to know about least?

Using these situations as endpoints on the following scale, please indicate for each of the other situations your relative desire to know about them, upon emerging from the isolated room. Indications may be made by placing the situations' numbers on the scale at the appropriate positions.

| least interested |                |                |                |                |                | most interested |
| finding out about |                |                |                |                |                | in finding out about |
Situations are sometimes monitored because they are instrumental for the attainment of goals and objectives. If a particular situation is in need of attention, it is an indication of the need for some sort of action, either to correct the poor condition of the situation; to respond with alterations in plans, programs, or actions that depend upon that situation; or to avail of opportunities that have arisen.

Using the following scale, please indicate for each situation the likelihood that the situation will be in need of managerial action at some time during the next three months.

<table>
<thead>
<tr>
<th>Situation #1</th>
<th>Situation #2</th>
<th>Situation #3</th>
<th>Situation #4</th>
<th>Situation #5</th>
<th>Situation #6</th>
<th>Situation #7</th>
<th>Situation #8</th>
<th>Situation #9</th>
<th>Situation #10</th>
</tr>
</thead>
<tbody>
<tr>
<td>very likely</td>
<td>very unlikely</td>
<td>to be in need</td>
<td>to be in need</td>
<td>of managerial</td>
<td>of managerial</td>
<td>action</td>
<td>action</td>
<td>action</td>
<td>action</td>
</tr>
<tr>
<td></td>
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<td>action</td>
<td>action</td>
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</tr>
</tbody>
</table>
Using the following scale, please indicate for each situation the value received during the past year from actions you have taken, as a result of formal and informal monitoring of the situation.

<table>
<thead>
<tr>
<th>of very little value</th>
<th>of moderate value</th>
<th>extremely valuable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Situation #1</td>
<td></td>
<td></td>
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<tr>
<td>Situation #2</td>
<td></td>
<td></td>
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<tr>
<td>Situation #3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation #4</td>
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<td></td>
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<tr>
<td>Situation #5</td>
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<td>Situation #6</td>
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<td>Situation #7</td>
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<td>Situation #8</td>
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<td>Situation #9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation #10</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
For which situation would you most hate to see something go wrong?

For which situation would you least hate to see something go wrong?

Using these situations as endpoints on the following scale, please indicate for each situation the relative degree of displeasure you would experience at seeing something go wrong. Indications may be made by placing the situations' numbers on the scale at the appropriate positions.

---

least hate to see something go wrong

most hate to see something go wrong
For which situation do you spend the most time monitoring?

#__________

For which situation do you spend the least time monitoring?

#__________

Using these situations as endpoints on the following scale, please indicate for each situation the relative degree of displeasure you would experience at seeing something go wrong. Indications may be made by placing the situations' numbers on the scale at the appropriate positions.

#__________  least time monitoring  #__________  most time monitoring
Which answer comes closer to telling how you usually feel or act?

If you were a teacher, would you rather teach

(A) fact courses, or
(B) courses involving theory?

Do you usually get along better with

(A) imaginative people, or
(B) realistic people?

Is it a higher compliment to be called

(A) a person of real feeling, or
(B) a consistently reasonable person

Would you rather have as a friend

(A) someone who is always coming up with new ideas, or
(B) someone who has both feet on the ground?

Do you usually

(A) value sentiment more than logic, or
(B) value logic more than sentiment?

In doing something that many other people do, does it appeal to you more to

(A) do it in the accepted way, or
(B) invent a way of your own?
Which word in each pair appeals to you more? Think what the words mean, not how they look or how they sound.

(A) gentle
   (B) firm

(A) statement
   (B) concept

(A) justice
   (B) mercy

(A) compassion
   (B) foresight

(A) benefits
   (B) blessings

(A) theory
   (B) certainty

(A) build
   (B) invent

(A) convincing
   (B) touching

(A) analyze
   (B) sympathize

(A) concrete
   (B) abstract

(A) who
   (B) what
Finally, we would like to ask you to describe your job. Please indicate the degree to which each of the following words or phrases describes your job.

<table>
<thead>
<tr>
<th></th>
<th>Describes the job not at all</th>
<th>Describes the job to a very great extent</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Strategic</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Operational</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Short Term Oriented</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Long Term Oriented</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Administrative</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Entrepreneurial</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Problem-Focused</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Opportunity-Focused</strong></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>